PREDICTING THE LIFE CYCLE OF RICE VARIETIES IN TEXAS

A Thesis

by

STEFPHANIE MICHELLE GAMBRELL

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

December 2004

Major Subject: Agricultural Economics

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Approved as to style and content by:

James W. Richardson (Chair of Committee)	David P. Anderson (Member)
David A. Bessler (Member)	Michael O. Way (Member)
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ABSTRACT

Predicting the Life Cycle of Rice Varieties in Texas. (December 2004)

Stefphanie Michelle Gambrell, B.S., Texas A&M University

Chair of Advisory Committee: Dr. James W. Richardson

The Texas rice industry has undergone many changes over the course of the industry's existence. Recently, high costs of production and the structure of government payments have contributed to a decreasing trend in rice acreage planted in Texas. While Texas was once the top rice producer in the United States, it now ranks fifth. Despite the fact that Texas has one of the lowest levels of production among rice producing states, it currently maintains the highest per acre yields.

One of the major factors in maintaining superior yields is the development of high performance rice varieties and hybrids, which provide increased yields on fewer acres. Research institutions invest a great deal of time, effort, and money towards the development of new varieties every year. Each one of these varieties has a specific set of traits that are believed to be in high demand by producers and processors. However, during the developmental stages, scientists are uncertain as to how each new gerplasm will perform once it reaches the market.

This study develops a regression model, which includes competition and the characteristics of a specific variety, to estimate the life cycle of new varieties and hybrids. In addition, simulation techniques are utilized to incorporate risk into the life cycle, providing a more robust prediction of the cumulative adoption and disadoption path.

Results indicate that the life cycle of new rice varieties is becoming shorter over time. Furthermore, the length of the life cycle is directly related to a new seed's performance, compared to other varieties on the market. Varieties that provide higher levels of performance, especially higher yields, tend to have a longer life cycle and achieve a larger market share, on average.

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As with any challenging task, I could not have made it down this long road without a support network. Thus, I feel it is extremely important to give thanks to the many individuals who have seen me through to the completion of my master's degree.

To begin with, I would like to thank my thesis committee for lending their wisdom to this young graduate student. I cannot imagine having dealt with a better collection of intelligent minds and kind personalities. Each one of you is truly an inspiration.

Dr. Richardson, I must say that you have been like a father to me. Whether I was a wide-eyed student in your undergraduate policy class or an undecided graduate planning the next step in life my life, I have always been able to depend upon your guidance and support. After all, I would not have applied to graduate school if I had not met you and been motivated by your research and teaching accomplishments. You have given me a job and led me toward a career during my time at Texas A&M, and for that I am extremely grateful. I only hope I can continue to make you proud as I venture to new places.

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supplemented with real world applications (and a few laughs). I know I will soon miss our frequent conversations and your lighthearted personality.

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CHAPTER I

INTRODUCTION

Rice production in the United States, and around the World, has experienced many changes over the last three centuries. According to the USA Rice Federation (2004), technological advances in the rice industry have allowed the United States to become one of the most innovative rice producing countries in the world.

Perhaps the most significant innovation in the area of rice production is the development of high yielding varieties and hybrid seed. New varieties and hybrids provide the potential for many changes to the industry, including higher yields and the possibility of price impacts, due to increased supply. Furthermore, improved cultivars lead to increased production on less land, which spares additional resources (i.e. water, labor, chemicals, and land) needed to sustain the world's population (Borlaug 2003).

Research institutions utilize a vast amount of resources during the rice development process, without knowing how long a new germplasm will remain on the market. Extension representatives in Beaumont, Texas indicate that breeding programs consume over half of rice research funding because 10 years are frequently required to develop a new rice variety, with estimated costs of $7-10 million (Clawson 1999). Each one of these varieties has specific traits that are believed to be in high demand by producers and processors. However, during the developmental stages, scientists are uncertain as to how each new variety will perform, once it reaches the market.

This thesis follows the style and format of the *American Journal of Agricultural Economics*.

Therefore, one can pose the simple economic question: Will the benefits outweigh the costs? Or, put another way, how many acres might be planted to a new variety, and will the sales revenue of the new variety outweigh the costs of development?

The risk and uncertainty inherent in the introduction of a new variety or hybrid makes predicting performance more difficult. Prior research has estimated predictive diffusion models, but researchers have rarely incorporated a risk component in their forecasts. Economic models involving rice variety development have estimated the profitability of established varieties and used these results as an indication of the potential profitability of a new variety in development. Although simulation modeling techniques have been utilized extensively in investment and adoption decision models, the use of simulation to predict the diffusion of a new technology is limited and is non-existent in the estimation of the acceptance of rice varieties. A predictive simulation model is needed to estimate a new rice variety or hybrid's potential life cycle.

Objective

The primary objective of this research is to predict the product life cycle, both cumulative adoption and disadoption, for new rice varieties and hybrids in Texas. To achieve this initial objective, the following specific objectives will be addressed:

- Determine factors which influence the diffusion, or life cycle, of established varieties, while incorporating the effects of competition;
- Estimate the life cycle of selected, established rice varieties;

- Apply simulation modeling techniques, using the traits desired for hybrids and varieties, to predict the producer acceptance of new seeds

Rice Production in Texas

The Texas rice industry generates approximately $500 million annually, making rice a significant contributor to the economic viability of the Gulf Coast (Wilson 2003). Texas ranks fifth among the states in annual production, surpassed by Arkansas, California, and Louisiana, and Mississippi. However, as the overall rice production in the United States has exhibited an upward trend over the past decade, Texas has shown a general downward trend. Figures 1.1 and 1.2 illustrate the production trends in the United States and Texas, respectively (NASS 2004).

New varieties and efficient production practices have provided farmers with higher yields on fewer acres. Although Texas is planting less land to rice, the state has maintained the highest per acre long grain rice yield in the nation since 1994. Along with better varieties, the current structure of government payments contributes to decreasing rice acres. Often times, Texas landowners can benefit more by removing their land from rice production, as to prevent sharing the government payment with a tenant (Clawson). Texas rice yield and acre trends are depicted in Figures 1.3 and 1.4 (NASS 2004). Faltering production coupled with “comparatively high costs (Clawson)” present a major obstacle for the Texas rice industry. In the end, current limitations provide further incentive for academic and private breeding institutions to develop lines of rice that will help the Texas rice infrastructure survive.

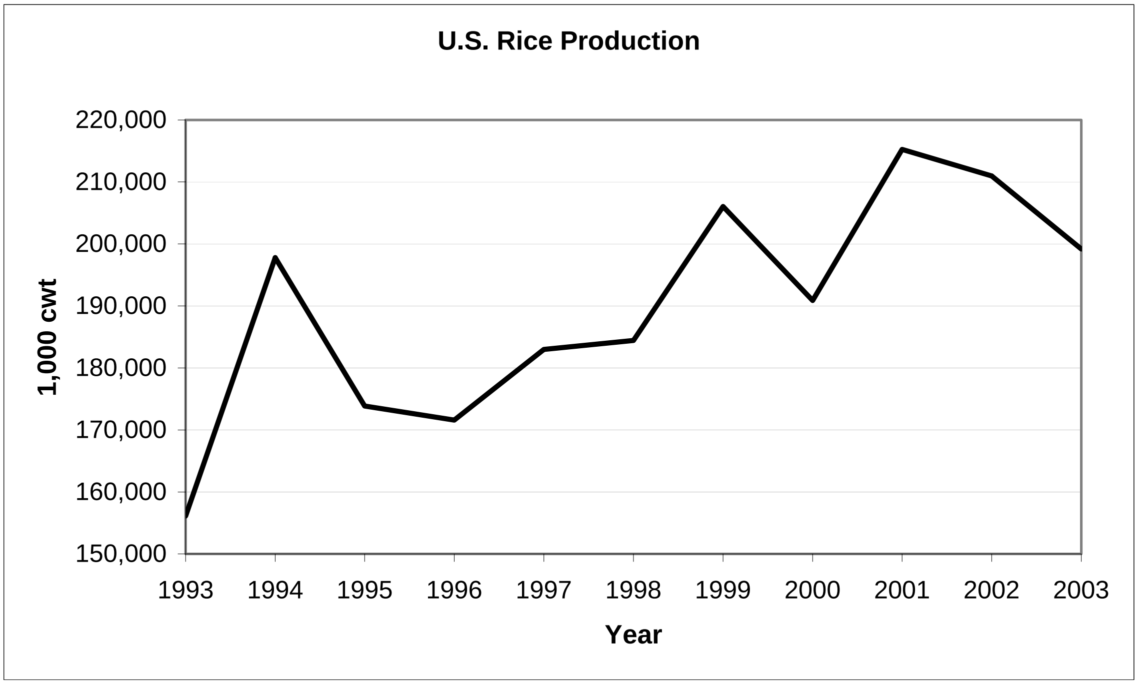

Figure 1.1. U.S. rice production 1993-2003. Data: NASS (2004)

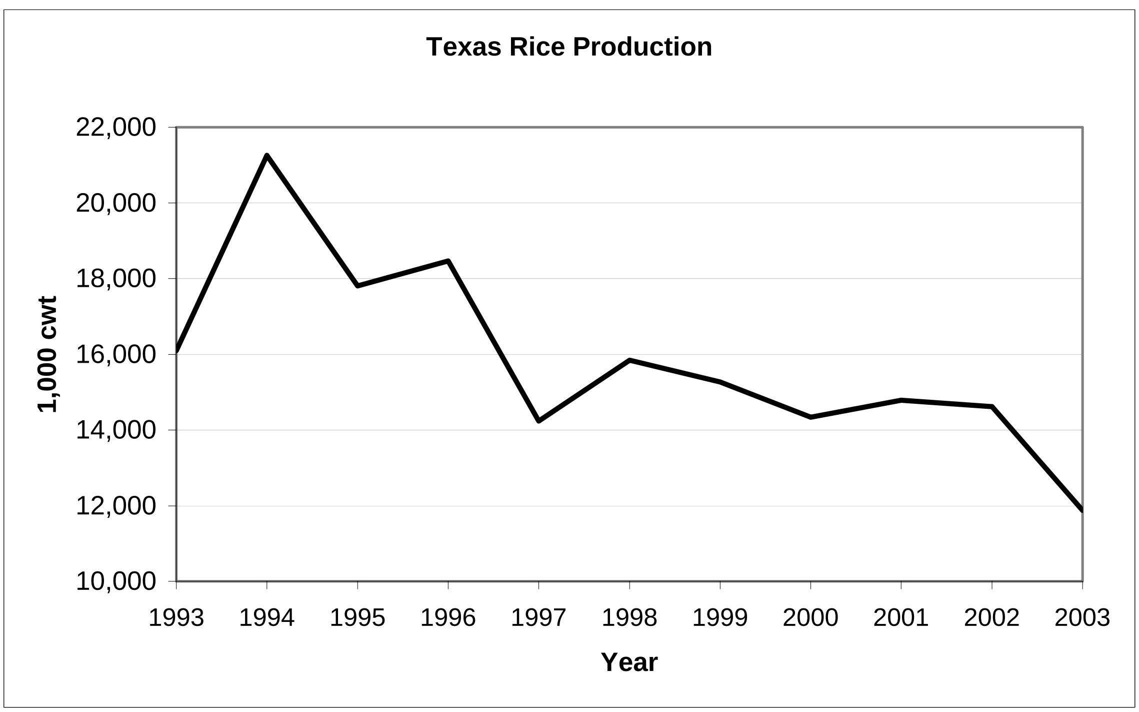

Figure 1.2. Texas rice production 1993-2003. Data: NASS (2004)

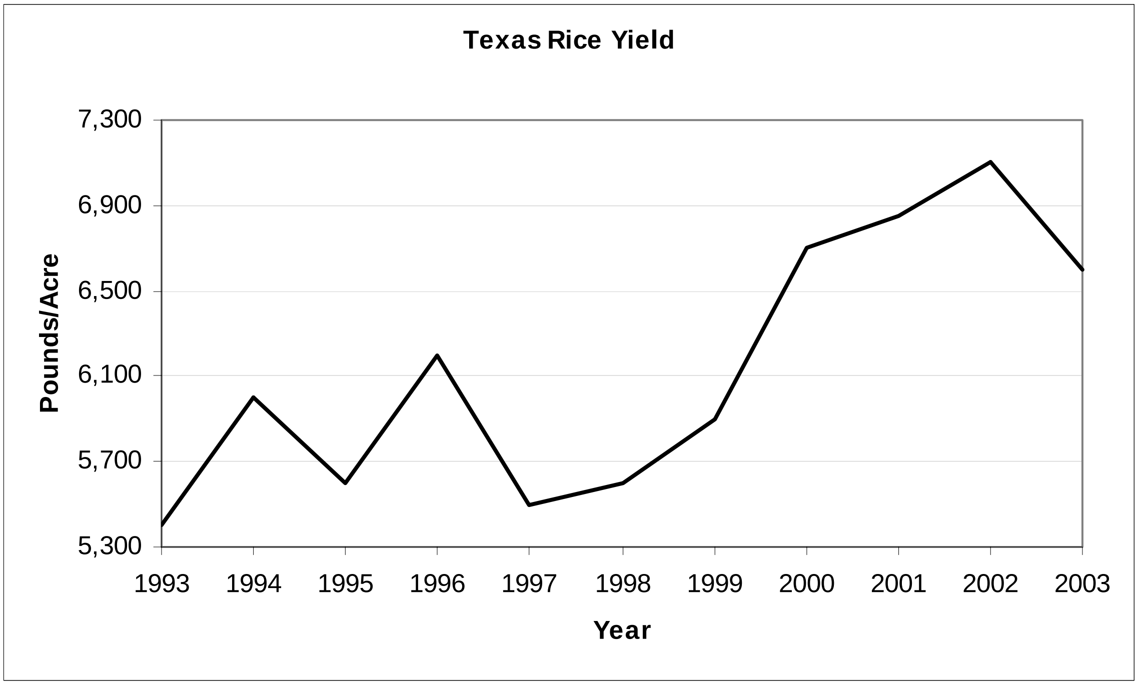

Figure 1.3. Texas rice yield 1993-2003. Data: NASS (2004)

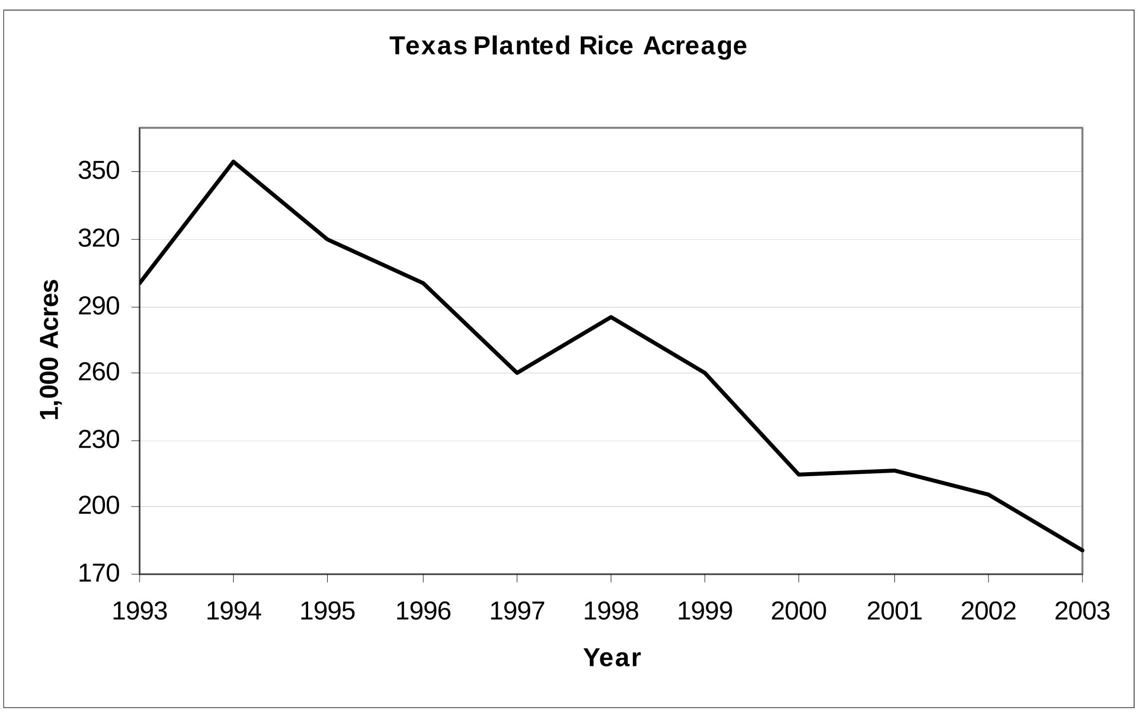

Figure 1.4. Texas planted rice acreage 1993-2003. Data: NASS (2004)

Rice Development

For the last forty years, rice breeders around the world, as well as in the U.S. and Texas, have provided farmers with higher performing seed varieties. Research conducted by the International Rice Research Institute (IRRI) in 1960 began paving the way for breeding research and the formation of better seed varieties (Dethloff 1988). The Institute's goal of resolving Asia's widespread hunger issues provided the rest of the world with indirect benefits. By 1966, the IRRI had made substantial progress, giving the world semi-dwarf rice varieties that were disease resistant and provided higher yields on fewer acres. Professionals in the rice industry fondly referred to the semi-dwarf varieties as a "miracle rice," leading the way towards a "Green Revolution" for crop production (Latham 1998).

The introduction of the variety Lemont in the early 1980's provided Texas with the first semi-dwarf rice variety to obtain wide spread commercial production within the state. Most breeders recognized the potential of the high yielding, semi-dwarf varieties, which were "targeted to the economic turnaround and future of the rice industry (Clarke 1984). Thus, with the success of Lemont, the extension centers, and some private firms, began placing a great deal of importance on plant breeding research.

While yield potential has traditionally been one of the most preferred rice characteristics to develop, current biotechnology allows scientists to focus on enhancing other traits including, but not limited to, disease and insect resistance, milling quality, plant size, grade, and taste characteristics. The most popular varieties in Texas for 2003 included Cocodrie, Cypress, CL161, and Jefferson, which represent 71.7, 10.0, 9.8, and

3.7 percent of planted acreage, respectively (Stansel and Clements 2004). Each of these varieties is an early maturing, long-grain semi-dwarf with high main crop, ratoon crop, and milling yield.

Yet, for all their success in capturing a large share of acres, each high performing variety has come and gone, supplanted by better varieties. The current study examines the variety life cycle, providing researchers with an analytical tool for use in variety development and marketing decisions.

Structure of Remaining Chapters

The remainder of this thesis is organized as follows. Chapter II contains a literature review on the adoption, diffusion, disadoption, and life cycle of new products. Chapter III discusses the methodology used to examine the cumulative adoption and disadoption of new rice varieties. Finally, Chapter IV contains the research results followed by the summary and conclusions in Chapter V.

CHAPTER II

REVIEW OF LITERATURE

The development of new technologies provides society with the chance to evolve by finding solutions to a variety of problems. The idea of progress fuels product development and has led to a great deal of research in the technology adoption and diffusion field, as can be seen in the reviews conducted by Feder et al. (1985), Mahajan and Peterson (1985), and Mahajan et al. (1990). As adoption and diffusion are two different concepts, the following review addresses these topics separately, followed by a section discussing the relatively smaller accumulation of disadoption and life cycle literature.

Adoption

In one of the seminal studies of adoption and diffusion, Rogers (1962, 1995) defines adoption as an "innovation-decision process" where an individual determines if a new technology is worthy of adoption. Rogers outlines the stages each person moves through leading to adoption as follows:

1. Knowledge of an innovation
2. Forming an attitude toward the innovation
3. Decision to adopt or reject
4. Implementation of the new idea
5. Confirmation of decision

The amount of time needed to move through this decision process can vary among individuals, which led Rogers to define the different adoption groups as innovators, early adopters, early majority, late majority, and laggards. Innovators forge the way in the adoption of a new technology, while laggards are skeptical and are the last to make an adoption decision.

One of the fundamental factors influencing the adoption decision is the level of commitment required. Some adoption decisions are dichotomous (adopt or not adopt) while others qualify as partial adoption (Feder et al.). Innovations falling in the dichotomous category tend to be machinery or production practices that require a large level of commitment or investment. On the other hand, there are innovations such as seed varieties and hybrids that can be adopted on a complete or partial basis. Related to this concept is the reversibility or irreversibility of the technology in question. Seed varieties and hybrids are examples of technology that can be partially adopted. In addition, it is reversible in that a farmer does not have to plant the same seed the following year.

Pindyck (1991) recognized that some investments are irreversible and their future value, or usefulness, is uncertain. Pindyck's research mentions that the irreversibility of an investment increases if the product is industry specific (machinery, production facilities, or equipment), has a low resale value, or is regulated heavily by the government. Thus, many individuals will postpone their decision to invest until new or better information becomes available. On the other hand, if the individual were to invest immediately, they now have an opportunity cost equal to the value of any future information. Ultimately, Pindyck's theoretical model shows that irreversible investment decisions are not made on a traditional net present value basis. The proper investment decision requires that "The value of the unit [of capital] must exceed the purchase and installation cost, by an amount equal to the value of keeping the investment option alive (p. 1112)."

The theory behind the timing of adoption decisions has recently been empirically tested in the literature (Purvis, et al. 1995; Isik 2001). In a study related directly to agriculture, Purvis et al. applied Pindyck's research on irreversibility and uncertainty to an empirical study of producers' investment decisions regarding free-stall dairy housing. While free-stall dairy housing provides increased milk production, it requires a rather large, partially irreversible investment. Future environmental regulations, leading to additional modifications, provide additional uncertainty. Therefore, producers are left with the difficult task of deciding the optimal time to invest or retaining the option to invest at a future date. Purvis (et al.) extended the Dixit-Pindyck model to estimate the value of an investment opportunity through simulation techniques, modeling the expected return from the free-stall housing as compared to the base, open-lot dairy. Results of the study indicated that producers were likely to postpone adoption of free-stall housing due to the uncertainty surrounding the cost of investment, which may be alleviated by cost-sharing government payments for best management practices.

Many studies have indicated that learning plays an important role determining the worth of a new technology and the adoption decision. In a study on the adoption of fertilizer responsive seed varieties, Hiebert (1974) described how learning alleviates the uncertainty inherent in the adoption of technologies. As Bayesian theory suggests, a potential adopter has a set of initial (prior) beliefs about a specific innovation, and as additional information is obtained, uncertainty about the innovation is reduced as prior beliefs are updated. Hiebert recognized that farmers are relatively unaware of the exact yield response to fertilizer for a new seed. Therefore, a farmer has the opportunity to partially adopt the new variety, acquire information about required input levels and their respective return, and adjust production practices based upon experience. As economic theory would suggest, Hiebert concluded farmers increase the amount of land planted with the new seed as their expected payoff from the technology increases.

Several researchers feel that learning is a dynamic component involved in the adoption decision process. Besley and Case (1993) and Cameron (1999) have suggested panel data, representing decisions made over time, best capture any household heterogeneity and can well represent the Bayesian learning processes. Thus, it is possible that cross-sectional and time-series analysis can lead to a biased estimation of an adoption model. However, Cameron's study found minimal levels of bias in cross-sectional estimates, yielding little support for this argument.

While economic and information variables are often influential factors in the adoption decision, an individual's perceptions about a technology's attributes play a large role as well (Adesina and Zinnah 1993; Adesina and Baidu-Forson 1995). The work of Adesina and accompanying authors utilized survey data to assess the impact of farmers' subjective preferences of modern rice seed varieties on adoption decisions in developing countries. Tobit model regression analysis revealed that quality characteristics such as yield, ease of cooking, tillering capacity, and ease of threshing were significant factors in explaining adoption. In a similar study, Sall et al. (2000) found the growing cycle, resistance to drought and disease/insects, cooking quality, and plant height to be important rice variety characteristics. Each of these articles comes to the conclusion that farmers' opinions are extremely important, and their input should be taken seriously in the plant breeding process. However, as Adesina and Baidu-Forson (p. 1) explained, there are many occasions where researchers lack survey data and must resort to "variables which affect farmers' access to information, and hence their perception information (e.g. extension, education, media exposure, etc.)."

Diffusion

The adoption of a new product, service, or idea by select individuals does not guarantee that it will be readily diffused throughout an industry or society. As noted before, adoption is an individual decision. Rogers (1995) defined diffusion as the communication of a technology throughout a social system, and identified the characteristics that determine an innovation's rate of adoption as follows:

1. Relative Advantage – Does the innovation have added benefits when compared to its predecessor?
2. Compatibility – Does the innovation conform to existing values and norms?
3. Complexity – Is the innovation difficult to understand or use?
4. Trialability – Can the innovation be tested or sampled?

5. Observability – Are the results of adopting the innovation visible to other individuals?

According to Rogers, “Innovations that are perceived by individuals as having greater relative advantage, compatibility, triability, observability, and less complexity will be adopted more rapidly than other innovations (p. 16).” However, when a new technology is introduced, there is a great deal of uncertainty as to how the product will conform to these guidelines. Therefore, as Rogers noted, the innovation must create enough interest to motivate individuals to seek information used to move through the “innovation-decision process” and determine whether the product is worthy of investment, or adoption. Eventually, as information is passed along and individual adoption decisions are made, the new technology will develop a diffusion path over time (usually S-shaped) that is dependent upon the rate of imitation in a specific society.

Mansfield (1961) asked the question, “Once an innovation is introduced by one firm, how soon do others in the industry come to use it (p. 741)?” In other words, what factors dictate why some firms choose to adopt a new technology quickly and other firms lag behind. Mansfield addressed the issue of the rate of imitation in a study of twelve production and transportation innovations in the coal, iron and steel, brewing, and railroad industries, most of which required a large financial commitment. It was hypothesized that the rate of imitation is a function of the number of firms currently using the innovation, the profits resulting from adoption, the size of investment, and “other” determinants. Mansfield utilized deterministic and stochastic logistic function models to estimate the S-shaped curve, or diffusion path, representing the number of firms that have not adopted each technology. Essentially, the least squares regression attempted to determine the proportion of firms that are “holding out” on adopting the new technology over time in the deterministic model, whereas the stochastic model estimated the probability that one of the “hold outs” would adopt in the future. In both the deterministic and stochastic models, results indicated that technologies with a larger number of prior adopters, greater profitability, and smaller initial investments lead to increased rates of imitation. However, as Mansfield points out, the validity of the stochastic model is questionable due to the small number of firms incorporated in the study. Including only large firms is not representative of an entire industry and cannot sufficiently predict the rate of imitation.

In a marketing study, Bass (1969) researched the timing of adoption and imitation of new, durable goods, which are purchased rather infrequently. The study separated adopters into two groups: innovators, who are initial adopters not influenced by others, and imitators, who learn from prior adopters. As such, the number of individuals who have already adopted the new product positively influences the timing of adoption and diffusion processes. Bass developed an exponential growth model to explain the growth in sales as a function of communication and time. As theory would suggest, results of the study indicated that sales grow rapidly in the beginning, reach a maximum, and eventually decline, yielding an S-shaped cumulative normal distribution.

Many additional studies in the field indicate that communication and learning play a large role in the diffusion of information and the widespread adoption of technologies. Ryan and Gross (1943) set the paradigm for empirical diffusion studies with a survey of corn farmers in two Iowa communities (Rogers 1995). Data showed that the "acceptance pattern" of hybrid seed followed an S-shaped distribution, which could be best expressed as a logistic function. Surveys indicated that, in the earlier years, salesmen were the most important influence on the dissemination of information and adoption. On the other hand, neighbors, who had already adopted corn hybrids and could provide advice, became more important in the latter years. Ryan and Gross stated the two main factors allowing the diffusion of hybrid corn to be a fairly rapid process are: corn hybrids are easy to test and adopt (or partially adopt) because there no major changes in production practices, and the diffusion of information about the new technology is a very social process through which salesmen, neighbors, and extension services contributed positively.

Feder and O'Mara (1982) obtained similar results in a study of high yielding varieties (HYV) where the diffusion of a new seed is dependent upon the producers' "accumulation of experience." As farmers obtain information from their neighbors and gain experience from planting a new variety, their prior beliefs are revised. Therefore, Feder and O'Mara assumed that the diffusion of an innovation could be modeled as a learning process where farmers' beliefs are updated in a Bayesian fashion. Due to an initial lack of experience, the authors stated that prior beliefs are based upon variables such as sales promotions, extension, education, and the profitability of current varieties. Over time, farmers' gain knowledge and make the decision to adopt when the expected profit for the new HYV is greater than or equal to the profit from the old variety. In the end, Feder and O'Mara concluded that the learning process becomes an integral element of the "aggregate adoption function" as uncertainty about the new variety decreases and more farmers adopt or fail to adopt the technology due to updated beliefs. Using both uniform and logistic distributions to define and update farmers' beliefs about a new technology, Shampine (1998) extended the theoretical Feder and O'Mara research to determine optimal levels of policy intervention with the goal of assisting in the spread of a new technology. Shampine found that most individuals learn about innovations rather quickly, leaving little need for intervention. However, one may speculate that as the level of investment required for a technology increases or the expected return from adoption is uncertain, the rate of adoption may decrease significantly.

Perhaps one of the most important variables to consider when analyzing the effectiveness, or diffusion, of a new technology is profitability. Therefore, it is imperative to discuss the seminal work in the area, that of Griliches (1957). Griliches was the first to utilize the logistic function in conjunction with economic theory to estimate the diffusion of hybrid seed. Similar to most new technologies, a graph of the percentage of acres planted with hybrids (cumulative adoption) indicated that the diffusion of modern corn seed resembled an S-shaped curve. Deciding that a logistic function would sufficiently fit the trend of the data, and would be easier to interpret than the cumulative normal, Griliches used log-linear regression methods (logit) to estimate the rate of adoption of corn hybrids in 31 states. The results of his study indicated that the diffusion of new corn hybrids depends upon farmers' expected profitability. As economic theory and profit maximization would suggest, the cumulative adoption of any given hybrid will increase as the farmers' potential for profit increases. Ito et al. (1992)

obtained similar results in a study replicating the Griliches methodology to assess the condition of the US rice industry. However, despite the widespread knowledge that this method was revolutionary in the field of diffusion economics, there has been some criticism of the logistic function used by Griliches due to the curve's inability to adjust to different potential adoption, or "ceiling," levels and non-symmetrical diffusion paths.

Dixon (1980) revisited the Griliches corn study, expressing concern over the validity of the ceiling values and estimation methods utilized in the original diffusion model. Griliches obtained fixed ceiling estimates by a visual inspection of data available in 1957, yielding ceiling values significantly lower than the actual full adoption population revealed by 1960 data. Furthermore, one could argue that the strict logistic function does not sufficiently fit the data for curves that tend to be skewed or non-symmetrical. With these concerns in mind, the Dixon study indicated that a ceiling value reflecting 100 percent adoption, used in conjunction with a non-symmetrical Gompertz function, results in a more accurate estimate of the diffusion of hybrid corn. Although Dixon utilized a fixed ceiling value (which is reasonable due to the fact that hybrid corn had reached full adoption long before publication), the study allows readers to make an important observation in comparison to the Griliches study. Static diffusion models can lead to misguided results.

Mahajan and Peterson (1978) noted that the ceiling value on the number of potential adopters could be affected by many factors such as population changes, marketing tools, and government action. Therefore, the study recommended diffusion ceilings be a function of important variables that may cause fluctuations in the potential number of adopters. Knudson (1991) incorporated methods from Mahajan and Peterson, as well as a Metcalfe and Gibbons (1983) study that showed diffusion ceilings can be represented as a function of a demand equation, to compare the performance of static and dynamic logistic diffusion models for semi-dwarf wheat varieties (SDWV). The dynamic Knudson model utilized a semi-dwarf wheat supply function to represent maximum number of adopters in any given wheat-producing state. Results of the study indicated that the dynamic model outperformed the static model, providing a better fit to the data. As Knudson indicated, the superior performance of the dynamic model is logical as it relaxes many assumptions inherent in the static logistic function such as allowing fluctuations in adopter population and adjusting to changes in the technology (i.e. prices) and its surrounding environment over time. With this in mind, dynamic models should be seriously considered when conducting a cumulative adoption study.

Methods Used

Although the terms adoption and diffusion are often lumped together in describing the success of new technologies, the analytical description of these two concepts takes on very different functional forms throughout the literature. Most often, probit-logit models are used in adoption studies to yield a binary, adopt or not adopt, decision, while the logistic function tends to be the preferred option to model cumulative adoption (Feder et al.). As mentioned earlier, prior research has estimated predictive diffusion models, but researchers have rarely, if ever, incorporated a risk component, as could be modeled using simulation techniques. Although recent research has shown that the potential ceiling of diffusion can vary in response to many factors, no studies have incorporated the fact that uncertainty in marketing a new technology can cause the rate of diffusion to become an uncertain path. The simulation literature is replete with applications to problems of risk and uncertainty, yet has not been applied to the projection of technology diffusion. This research pulls together the diffusion literature and simulation to explore the dynamic diffusion path under uncertainty.

The topic of diffusion has been covered extensively in several reviews and surveys. The following section uses the notation found in Mahajan and Peterson (1985) and Knudson (1991) to describe the most common models used in empirical diffusion studies. The basic diffusion model, which most cumulative adoption studies build upon, can be represented as:

$$dN(t)/dt = g(t)\ [N^M\text{-}N(t)]$$

where $dN(t)/dt$ indicates the rate of diffusion at time t, $N(t)$ is the cumulative number of adopters at time t, N^M is the maximum number of adopters at time t, and $g(t)$ is the coefficient of diffusion. It follows that the number of potential adopters in the social system at time t is $[N^M\text{-}N(t)]$. Although it is clear that the basic model focuses on time as an explanatory variable, theory would suggest that several other factors could play a role in a social system's adoption of a new technology. As Mahajan and Peterson point out, any additional influential factors such as communication, differences in the social system, and characteristics of the technology will be captured in the coefficient of diffusion, $g(t)$. Thus, the functional form of $g(t)$ is indicative of the approach taken toward various descriptive variables.

When adoption in time t is not dependent upon prior adoption, meaning the social system does not rely on communication between adopters and non-adopters, $g(t) = a$ yielding the following function called the *external influence model*.

$$dN(t)/dt = a\ [N^M - N(t)]$$

Lack of communication in a social system requires that adopters learn about a new technology from external sources such as mass media or extension efforts, which are captured in the constant term, a. On the other hand, the *internal influence model* defines a social system where communication between prior adopters and potential adopters becomes the central factor in the diffusion process. Mahajan and Peterson show that $g(t)$ is now defined as $bN(t)$, allowing for interaction between prior adopters, $N(t)$, and potential adopters, $[N^M - N(t)]$. The resulting equation is as follows.

$$dN(t)/dt = bN(t)\ [N^M - N(t)]$$

The internal influence, or imitation, model is a logistic function found in many diffusion studies, including Griliches (1957). Finally, some researchers have combined the aforementioned models to create a *mixed influence model*, which displays joint effect of internal and external influences. Mahajan and Peterson depict the mixed influence model as follows:

$$dN(t)/dt = (a + bN(t))\ [N^M - N(t)]$$

where the a term captures influences external to the model and the b term represents internal influences. The mixed influence model is prevalent in the marketing literature. Bass (1969) utilized a mixed influence model to forecast the sales of durable goods, thereby creating one of the most popular new product growth models to be used in the marketing field.

It is important to note that some researchers (i.e. Dixon 1980) have expressed concern over using a logistic function, which is naturally symmetric about an inflection point of 0.50. One alternative method is to utilize a Gompertz function, imposing an inflection point at 0.37 through the use of a log transformation on the number of potential adopters, [log N^M-$N(t)$]. A lower inflection point on the diffusion curve implies earlier adopters are more decisive and adopt a new technology at a faster pace. Therefore, the maximum diffusion rate takes place at an earlier stage. However, when studying farmers in a specific area (i.e. Texas), it is reasonable to assume the social system will communicate well over close distances, resulting in a symmetrical diffusion path (Mahajan and Peterson; Knudson). Therefore, the logistic equation is an appropriate measure of the diffusion process.

Griliches represented the diffusion of hybrid corn seed with respect to time as follows:

$$dP/dt = -b/(P/K)(K-P)$$

where P represents the percentage of land planted to hybrid seed, K is the ceiling or maximum level of adoption, and b is the rate of diffusion. Through algebraic manipulation and the use of logarithms, Griliches displayed the logistic diffusion equation in terms easily estimated through least squares regression.

$$\log_e [P/(K-P)] = a + bt$$

Although the models listed above have been deemed as sufficient methods of diffusion estimation, the process through which the ceiling value is obtained has been a source of debate. The Griliches model obtained a ceiling value through a somewhat arbitrary linear interpolation method, by way of visual inspection. As the ceiling value can be influenced by many different factors (Mahajan and Peterson 1978), the preferred parameter estimation method allows for flexibility in the maximum number of adopters and the resulting shape of the diffusion equation.

Knudson set forth a dynamic diffusion model where the ceiling, or maximum number of SDWV adopters, was represented as a semi-dwarf wheat seed supply function, $y(t)$.

$$y(t) = f(pr(t), pp(t), pf(t))$$

The supply function incorporates the price farmers receive as $pr(t)$, the price farmers pay for SDWV seed is $pp(t)$, and the price farmers pay for fertilizer is $pf(t)$. As indicated by Majahan and Peterson, the ceiling becomes a function of a vector, $f(s(t))$, composed of influential factors having an impact upon N^M. Thus, the maximum number of adopters remains dynamic over time.

Disadoption and Life Cycles

When considering the topics of adoption, diffusion, and disadoption, the latter has received far less attention in the literature. Similar to the choices made at the onset of purchasing a new product, where multiple individuals make an adoption decision resulting in diffusion, adopters must also decide whether to continue using, or purchasing, a product.

Many diffusion models using a logistic function, such as the original 1969 Bass model, do not allow for the possibility of disadoption. Mahajan et al. (1990, p. 15) state, “The objective of a diffusion model is to represent the level or spread of an innovation among a given set of prospective adopters.” Therefore, many studies are only concerned about predicting the number of first time purchases, as to estimate a product’s rate of growth. However, an increasing number of researchers have realized effective diffusion models need not only include first time adopters, but must also consider repeat purchases and the eventual disadoption of a product to properly estimate sales potential over the entire life cycle.

Many studies have attempted to modify logistic functions, such as the Bass model, to incorporate repeat purchases and/or model disadoption. Olson and Choi (1985) conducted one of the first studies that included replacement purchases in the original Bass model, in addition to first time purchases. When durable goods, such as dryers, break down, most customers will purchase a new unit to fulfill the same needs. Olsen and Choi assumed customers use a durable good for a fixed period of time, upon which the unit breaks and a new version is purchased. Therefore, repeat purchases can be easily predicted after quantifying the number and timing of first time adoptions. However, the model provides no consideration for random problems in the performance of a durable good, which leads to underestimation of the number of replacements and can misrepresent the length of the product life cycle. Kamakura and Balasubramanian

(1987) expand upon the Olsen and Choi study, relaxing the assumption that the life of a durable product is known a priori. Replacement purchases were modeled using an additional “demand component,” which allowed for product failure at the end of the expected life cycle as well as every point in time after purchase. As logic would dictate, failure rates were allowed to increase with the passage of time.

While the aforementioned studies included the potential for repeat purchases, they failed to incorporate the possibility of disadoption and eventual discontinuation of a product. Lilien et al. (1981) present one of the first models accounting for the disadoption of a product. The study incorporates Bayesian procedures to update prior information and allow for repeat purchases or the disadoption of ethical drugs. While the model includes the impacts of competitive advertising in the market and the potential for switching to a competitor’s product, the main focus of the study is the introductory phase of an ethical drug. Thus, the disadoption period is not given a great deal of attention, and the resulting function is very similar to other S-shaped diffusion functions that rely on a fixed ceiling level of adopters.

In a study of the diffusion of integrated circuits sold within the industry sector, Norton and Bass (1987) modified the original Bass logistic function an incorporated methods from the Fisher and Pry (1971) and Blackman (1971) substitution models, where successive generations of a product are allowed to replace older versions. The study found that the adoption pool consists of repeat purchasers who continue to use the old technology, switchers who choose to upgrade to the newer technology after having used the old version, and first time adopters who have never purchased the product but decide to purchase the newest version. Thus, one can observe a separate diffusion path for each successive generation with the potential for movement from one type of integrated circuit to another. However, the Fisher-Pry and Blackman models assume movement to a new generation is somewhat terminal. Due to the fact that integrated circuits are a highly technical product, switchers are assumed to never revert to a prior generation after a change has been made. Therefore, while this model works extremely well for highly technical products sold within the industrial sector, the method may prove rather strict when considering the consumer sector where switching from one product to another is not necessarily a one-way street.

Although many life cycle studies tend to focus on the growth stage, there are an increasing number of studies that take a step back to look at the complete product life cycle. The product life cycle, in its entirety, embodies first time adoption, repeat purchases, brand switching, and the disadoption or decline of a product. Despite the fact that a firm can make a great deal of money during the growth phase, companies still have the opportunity to capture a return on their investment via sales in the product decline stage. With this in mind, it becomes important to understand the potential length of the product life cycle.

With the onset of technological advancement and the continual introduction of better products, the life cycle is sure to become shorter over time due to competitive forces. Qualls et al. (1981) present the first empirical evidence of shortening life cycles in a study of 37 household appliances over the years 1922-1979. To provide units of comparison, the time frame was divided into three periods in which there were several similar product introductions. The study uses the length of the growth and introduction phases as a proxy for the length of the entire life cycle. Results of the study indicated a significant difference in the cycle length of the appliances within the three time periods, with a six and five fold decrease in the average length of the introductory and growth stages, respectively.

Some recent studies in agriculture have begun to take notice of shorter life cycles of new seed varieties. Dooley and Kurtz (2001) recognized potential problems inherent in the shortening life cycle of corn hybrids. The study addresses the changes in costs incurred by U.S. seed companies when struggling to manage a larger number of hybrids with varying levels of demand. Dooley and Kurtz made use of the Blackman (1971) method to estimate the demand of varieties throughout their product life cycle. Seed production and inventory costs were then simulated, based upon the average demand across an eight and five year period, which represented the typical hybrid corn life cycle length in the mid-1990's and year 2000, respectively. Results indicated that a shorter life cycle had the potential to increase total inventory costs by 120.8 percent. Although one could question the use of the Blackman model, which is normally associated with industrial products and substitution caused by a rather large technological innovation, the study is a major step forward. Perhaps the most important aspect of the study is the use of stochastic demand and inventory cost variables, which created a more complete estimate by incorporating uncertainty into the model.

Kinwa-Muzinga and Mazzocco (2002) took an interesting approach to estimating industry impacts due to shorter life cycles of various biotech corn seeds. The study formulated a dynamic programming model to discover the preferred price path for a portfolio of corn seeds, while considering the shorter life cycles of each respective seed. The model made use of several state variables to incorporate variety characteristics, competition, and substitution. The most interesting variable used in the study is a marketing mix ratio, comparing the level of marketing efforts of a specific firm to other firms in the industry. Thus, the model directly incorporated competition, which has the potential to affect price paths and the length of product life cycles. The results of the study indicated seed firms have the greatest level of returns when the firm has a relatively strong presence in the market, strong perceived benefits with respect to new varieties, and can maintain equal or superior marketing efforts compared to other firms. However, as the author noted, the results of the study may be slightly misleading due to a fixed percentage of repeat purchases and adopting market size. Despite these drawbacks, the study is a major step toward finding new applications for life cycle research.

Summary

The literature pertaining to adoption and diffusion is quite extensive with substantial research dating all the way back to the 1940's. Early studies seemed to focus on generalizations about the shape of the diffusion curve and individual adoption decisions. Revolutionary studies by Griliches, Mansfield, and Bass were the first to utilize the logistic function to estimate the diffusion, or growth path, of new innovations.

Thereafter, the majority of the studies in the area of diffusion have continued to use some form of the logistic function.

In the 1980's studies began to indicate the importance of flexible ceiling levels, a technology's specific traits, and the substitution between technologies in providing a more dynamic model. However, most diffusion research deals with durable goods or entire classes of products (i.e. washing machines, jet engines, or corn hybrids). Thus, product switching is approached as a movement from one generation to another, as opposed to competition between "brands."

More recent research in agriculture has indicated the importance of studying competition, life cycles and disadoption. With the rapid level of innovation and the increasing competition within the seed industry, product life cycles have grown shorter. However there has been no research on estimating the life cycles of specific types of rice seed and the interaction between these products. In addition, former studies of rice varieties have focused solely on the growth phase of the product, lending no insight to the future disadoption of each variety. There is a need for research that incorporates the effects of competition, based on product specific characteristics, providing the possibility for the disadoption of substandard varieties. Therefore, this study will add to the current literature, developing a model that predicts the dynamic product life cycle of various rice varieties, including competition between varieties.

CHAPTER III

METHODOLOGY

Predicting the acceptance of specific rice varieties in Texas was initially approached with the goal of incorporating prior diffusion methods, Griliches and Knudson, and simulation techniques to provide a more robust estimate of diffusion. However, upon inspection of the acreage data specific to the producer acceptance of individual varieties, it became apparent that prior methods used in the estimation of seed diffusion are deficient in an important area, the disadoption of technology. Figure 3.1 displays the life cycle of the Lemont variety in Texas from its introduction in 1983 to 2001 (TAES 2004a). Acres planted to Lemont increased for the first 6 years following release, then declined as other improved varieties were introduced. It is this complete life cycle that is of interest for this study, as the economic success of any given variety is dependent upon both the adoption and abandonment processes.

Griliches' and Knudson's work, along with most other studies, displayed an S-shaped diffusion path because they examined a whole class of varieties – hybrid corn and semi-dwarf wheat varieties, respectively. Therefore the logistic function fit the data well, due to the fact that a superior product class was not in existence to cause the disadoption of all hybrid corn and semi-dwarf wheat. On the other hand, specific varieties within those classes could exhibit a general bell-shaped, or increasing and decreasing, pattern throughout their cumulative adoption and disadoption phases.

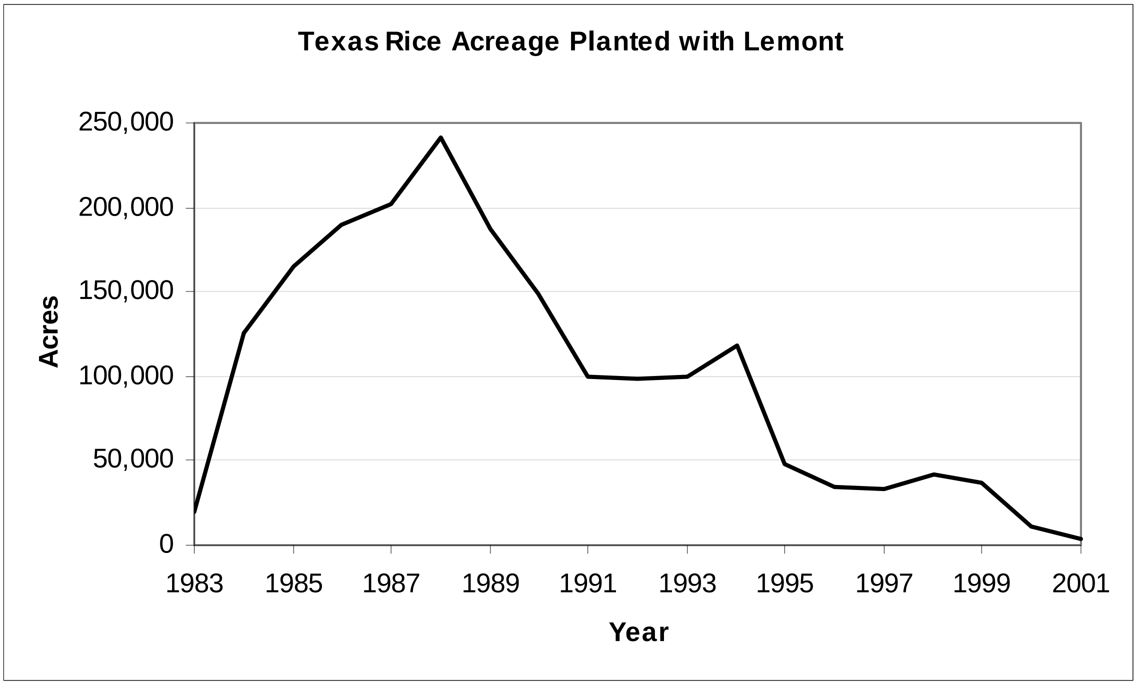

Figure 3.1. Texas rice acreage planted with Lemont 1983-2001. Data: TAES (2004a)

As discussed in the literature review, a great deal of effort has been expended to modify early diffusion models to incorporate repeat purchases, switching from one product to another, and disadoption. However, the relatively more flexible models such as Fisher-Pry, Blackman, and Norton-Bass are better used for revolutionary innovations from which there is little chance of turning back. For example, individuals who move from horses to tractors for farm work, from bulky cellular phones to compact cellular phones, or even from regular rice varieties before 1960 to high performing semi-dwarf rice varieties are unlikely to revert back to the original product after switching. Furthermore, the majority of all logistic-based diffusion equations use a fixed maximum cumulative adoption level, which is not feasible for a number of industries.

For this research, there must be the opportunity for the joint use of more than one product. Despite the fact that a specific variety is superior to others on the market, many producers choose to grow more than one variety at a time, perhaps due to contract reasons, time to maturity and harvesting constraints, or because the older varieties are familiar and provide some level of security. As the industry becomes more comfortable with the newer varieties, whether through experience or advertising efforts, there is an increased potential for the seed to capture the majority of the total acreage. However, there is no guarantee that the industry will completely transition into using only one variety, without reverting to the use of a former variety after a trial and error process. In addition, the model cannot have a pre-determined maximum level of adoption. In Texas, the number of acres planted to rice (the ultimate user of the seed) is clearly changing over time, making a fixed ceiling level illogical.

Therefore, this paper will move away from the logistic equation to provide a less restrictive model, which considers the effects of competition and captures the complete life cycle of "brands" within a product class. Finally, the predictive ability of the model will be enhanced through the use of simulation.

Data

Data in this study were collected with the goal of determining the performance of specific varieties relative to the market in Texas. As long-grain rice encompasses the majority of production in Texas and the United States, only long grain varieties were included in the study. Table 3.1 indicates the data collected, variable names (used in formulation of the model revealed in the following section), and the sources of each variable.

Table 3.1 Data and Sources for Life Cycle Estimation of Varieties in Texas

Data	Variable	Source
Percent of Total Acres Planted	% Acres	TAES
Yield per Acre	Yield Ratio	TAES Producer Surveys TAES/USDA Test Plots
Milling Yield - % Whole Kernels	Milling Yield Ratio	TAES Producer Surveys TAES/USDA Test Plots
Days to Maturity	Maturity Ratio	TAES/USDA-ARS Test Plots
Yield Stability	σ Yield Ratio	TAES/USDA-ARS Test Plots

σ = Standard Deviation
TAES = Texas Agricultural Experiment Station
USDA = United States Department of Agriculture
ARS = Agricultural Research Service

The Texas Agricultural Experiment Station (TAES) in Beaumont collects several data sets on rice annually. Researchers at the Rice Miller's Association and TAES have monitored the percent of acres planted, by variety, for over fifty years. However, this study is concerned with more recent rice varieties and will only consider market share of varieties introduced from 1983-2003. In addition, producer and miller surveys from 1996-2003 provide data indicating the performance of specific varieties with respect to variables such as yield per acre, milling yield as percent of the total crop, and grade (TAES 2004b). Finally, test plot data collected from research in various locations within Texas from 1983-2003 provides additional observations for yield per acre, yield stability, and days to maturity (USDA-ARS 2004).

Life Cycle Model Formulation

In this thesis, the life cycle of a variety is predicted by estimating the percent of total rice acres in Texas planted to that variety. There are several factors that are hypothesized to influence the life cycle of varieties, but first it is important to inspect the rice market share data over the past twenty years. Figure 3.2 depicts six rice varieties that comprise the majority of recent rice production. There are two important things to mention about this graph.

First, the life cycle of rice varieties is clearly growing shorter over time. For example, Lemont has a life cycle that spans nearly 20 years. On the other hand, Jefferson's life cycle is only 7 years long. This trend of shortening life cycles falls in line with observations made by Dooley and Kurtz (2001) and Kinwa-Muzinga and Mazzocco (2002) in the corn industry, which is displaying life cycles of 5 or 6 years. Although corn seed research has generally been more progressive than rice seed, due to the high level of corn production in the U.S., rice is likely to follow the same life cycle trends as the number of varieties steadily increases.

Second, upon introduction, each new rice variety appears to receive approximately three years to remain unchallenged by the introduction of a new variety. Although numerous varieties may be in use at the point of introduction, and throughout a new variety's life cycle, it may be safe to assume that new seeds are given three years of lead time.

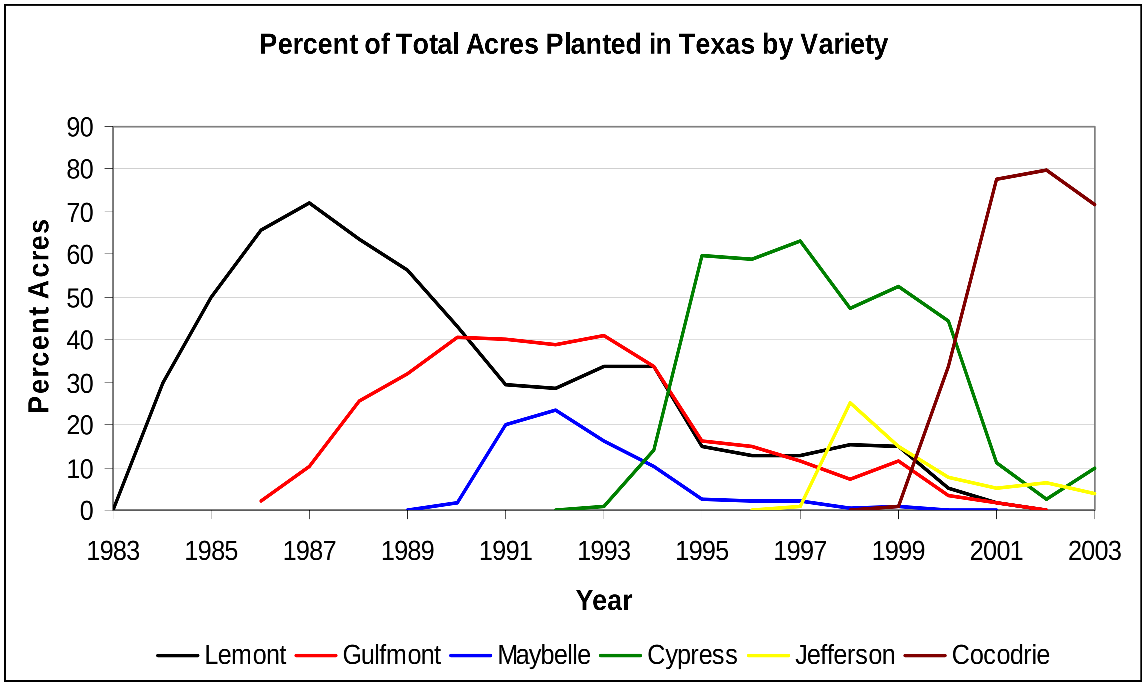

Figure 3.2. Percent of Texas rice acreage by variety 1983-2003. Data: TAES (2004a)

With the aforementioned trends and characteristics in mind, the following model is hypothesized to predict the life cycle of rice varieties,

$$\%A = \beta_0 + \beta_1 \%A_{t\text{-}1} + \beta_2 YR + \beta_3 MYR + \beta_4 MR + \beta_5 \sigma YR + \beta_6 T + \beta_7 T^2 + \beta_8 T^3 + \varepsilon \quad (1)$$

where $\%A$ is the percent of acres planted to a variety in Texas, $\%A_{t\text{-}1}$ is a one year lag of the percent of acres planted by variety, and the T variables represent the number of years a variety has been in existence. The three time variables are hypothesized to capture the cyclical movements seen in Figure 3.2. In addition, several ratios are included in equation 1 to model the competition between different varieties, based upon certain performance characteristics producers look for when purchasing seed. Equation 2 displays the basic form each performance ratio assumes, using yield (YR) for illustration.

This thesis examines the diffusion of specific rice varieties, as opposed to variety classes in the previous literature. Using simulation techniques to incorporate risk into the diffusion path, new variety product life cycle diffusion is projected with implications for breeders, researchers, and private companies.

$$YR = \frac{Yield\ Variety\ A}{Yield\ Next\ Best\ Alternative} \tag{2}$$

The use of ratios allows for the direct comparison of a specific variety to other varieties in existence. For example, suppose a new variety "*A*" is introduced with the highest yield performance available. When variety *A* is compared to the next best alternative on the market, variety *A*'s yield ratio will be greater than one. As higher yielding varieties are introduced over time, the yield ratio of variety *A* will decline, accordingly. However, if variety *A* is introduced with a substandard yield, relative to current varieties, its yield ratio will be less than one from the start. Thus, a variety's life cycle depends upon its performance, with respect to other varieties that are available. Although this ratio method was formulated prior to finding any such procedure in the literature, the use of ratios to model competition is supported in the Kinwa-Muzinga and Mazzocco (2002) study.

There are several performance characteristics that are hypothesized to influence the life cycle of new varieties and are represented as ratios in equation 1. To begin with, yield tends to be the most important factor in a producer's choice of rice varieties (McClung 2004). High yields per acre provide producers with the potential for increased revenue. As revenue is equal to *price* x *production*, and production is equal to *yield* x *acres planted*, yield becomes a proxy for revenue and can represent some of the economic reasoning within the industry. Furthermore, yield is a proxy for other variables, such as disease and insect resistance. As the pest and disease resistance of varieties increase, the plants are less stressed and can potentially have higher yields. Ultimately, the yield ratio (*YR)* is expected to positively influence the percent of total acres planted to each variety.

Although milling yield is closely related to the overall yield of a variety, it is a characteristic that is likely to have an impact on the cumulative adoption and disadoption of varieties. When rice is taken to the mill, producers receive better grades for whole, or unbroken, kernels. The base price received for all rice varieties may be the same, but varieties resulting in a higher percent of whole kernels provide the potential for price premiums. Despite this fact, many producers tend to focus on quantity over quality. Often times, producers can make up for lower quality if the chosen variety has larger yields. Thus, it would not be surprising to see yield overshadow the influence of milling yield. Nevertheless, the milling yield ratio (*MYR*) should be positively related to the percent of acres planted.

In addition, the number of days until the rice plant reaches maturity is viewed as being important within the industry. Varieties that mature earlier provide the opportunity to harvest a second, or ratoon, crop within the same season. In addition, if a variety matures earlier, there is less time for disasters such as pest attacks, disease epidemics, and hurricanes to adversely affect the crop. On the other hand, the maturing period must be long enough for the plant to fully develop and achieve its yield potential. With this in mind, varieties that mature reasonably early allow the potential for decreased risk on the main crop. Due to ease of measurement, the number of days to heading tends to be the preferred measurement used at experiment stations to indicate the earliness of maturity. Thus, for this research, the time of maturity is measured by the number of days until the varieties head, or the panicle emerges for pollination. As fewer days to maturity is generally preferred, the maturity ratio (*MR*) is expected to have a negative relationship with the percent of acres planted.

Finally, it is logical to believe that the stability of a variety's yield could have an impact on the seed's acceptance. If the yield per acre is highly variable from year to year, the industry may perceive the variety as too risky. The standard deviation of each variety's yields per acre, across several locations in Texas, is hypothesized to be a good estimate of the relative stability of each variety in existence. Smaller standard deviations represent a variety with more stable yields. Therefore, the stability ratio (σY) should be negatively related to the percent of acres planted. Despite the logical reasoning behind incorporating yield stability, it is important to note that the producer data set available is not sufficiently detailed to calculate this variable. The producer yields provided in the surveys are representative of the entire state of Texas and are not broken down by location. Although yield stability would likely enhance the model, the data do not allow for the possibility, at this time. Therefore, the model used in estimation becomes equation 3.

$$\%A = \beta_0 + \beta_1 \%A_{t-1} + \beta_2 YR + \beta_3 MYR + \beta_4 MR + \beta_5 T + \beta_6 T^2 + \beta_7 T^3 + \varepsilon \qquad (3)$$

Model Estimation Procedures

The varieties included in the model estimation, in order of their introduction, are Lemont, Gulfmont, Maybelle, Cypress, Jefferson, and Cocodrie. Together, these varieties represent the majority of the rice production in Texas over the past 20 years. To capture the influence all six varieties, cross-sectional OLS regression analysis is used, in which the data for each variety are stacked in the order of their introduction. In addition, the model contains a time series component within the *T* variables, representing the amount of time each variety is in existence.

Two models are estimated using the data on hand. The first model estimates the life cycle of a variety, equation 3, utilizing an average of the available producer survey data from 1996-2003 for the *YR* and *MYR*[1]. No producer data are available for the number of days to maturity so test plot data will be used as a proxy for the *MR*. In this initial model, the producers in the industry are relying solely on their own, collective, experience. Thus, the model is referred to as the model "without prior."

The second model will incorporate test plot and producer survey data to estimate the life cycle. In the first two years of a variety's existence, an average of the test plot data, prior to the variety's introduction, is substituted for producer data to estimate the *YR* and *MYR*. At the onset of the third year, the average of the producer survey data is utilized. Hypothetically, the second model gives the industry some prior knowledge of the variety's performance upon its introduction, which is updated with producers'

[1] It is important to note that the range of producer data is limited. Staff at TAES indicated that the miller and producer surveys began in 1996. However, the author feels it is important to include the collective experience of producers in the model. Thus, the average of available data is used for the *YR* and *MYR*.

experience as time passes. Similar to the initial model, test plot data must be used to estimate the *MR* and cannot be updated, due to a lack of producer data. The second model is referred to as the model "with prior."

Finally, the equations estimated for the aforementioned models, both with and without prior information, are paired with simulation techniques to predict the life cycle of a new variety.

Simulation Model

As mentioned before, there is a great deal of risk and uncertainty involved in the life cycle of a new technology. Basic diffusion models and point forecasts provide merely one of many potential outcomes. On the other hand, simulation can be used to statistically represent the possible combinations of random variables in a system (Richardson 2004). Thus, incorporating a risk component into a life cycle equation can provide a probability distribution about one's forecast, creating a more robust prediction of the varieties' acceptance.

Inherent in the estimated life cycle equation is an error term that defines the probability distribution about the cumulative adoption and disadoption path. Under the assumption that the residuals, captured within the error term, are normally distributed in equation 3, the life cycle could be made stochastic and simulated.

One can hypothesize that the variability in the percent of acres planted to a specific variety is not constant over time. At a minimum, the distant future is more uncertain than the near future. Therefore, a separate empirical distribution is created for each year of the life cycle using the residuals of the six varieties included in the estimation of equation 3. Thus, this method does not assume a constant variation in acres over the course of a variety's adoption and disadoption. Instead, the percent of acreage planted will be allowed to fluctuate in each year, providing a more realistic representation of the product life cycle. With that said, although each year has a separate probability distribution, one can expect each year to be somewhat correlated to the next. Therefore, the deviates in each year are appropriately correlated before simulations are conducted.

Finally, as mentioned previously, each new variety gets approximately three years to be a potential leader, without the interruption of new variety introductions. To represent the dynamic nature of the seed market in simulations, a variety's ratios will remain constant for three years and then decline to capture the existence of newer varieties.

CHAPTER IV

RESULTS AND DISCUSSION

The results chapter is divided into three main sections. The first portion provides the model estimates and discusses the steps taken to refine the models, both with and without prior expectations as an explanatory variable. The next section explains the results of out of sample modeling and compares the performance of the two models. Finally, the last section reports the simulation results.

Model Estimation

The six varieties included in the estimation of the models provide 70 observations for use in the cross-sectional analysis. The regressions are performed using Simetar, a statistics and simulation Excel ad-in package developed at Texas A&M University. In this section, the estimation of the model without prior is discussed first, followed by the model with prior and a comparison of the two models' performance.

Without Prior

Table 4.1 displays the parameter estimates and test statistics from the regression output. The estimation resulted in a good fit for a cross-sectional model, with an R^2 of 0.809. In addition, $\%A_{t-1}$ and *YR* are significant and have the expected signs, both having a positive effect on the percent of acres planted to a variety. On the other hand, *MYR* and *MR* resulted in signs opposite to those hypothesized, but the variables were insignificant in the regression.

Table 4.1. Parameter Estimates and Statistics for Full Model, Without Prior

Variable/Test Statistic	Estimate
Constant	-36.778
	(34.872)[a]
$\%A_{t-1}$ (Percent Acres in t-1)	0.761**
	(0.084)
YR (Yield Ratio)	41.747*
	(21.756)
MYR (Milling Yield Ratio)	-4.503
	(32.346)
MR (Maturity Ratio)	15.774
	(15.271)
T (Time)	-0.166
	(4.067)
T^2 (Time^2)	-0.191
	(0.430)
T^3 (Time^3)	0.009
	(0.013)
R^2	0.809
SIC	5.012
DW	1.857[b]
MAPE	213

*Denotes significance at the 0.10 level.
**Denotes significance at the 0.05 level.
[a] Numbers in parentheses are standard errors.
[b]Upper Critical Value (T=70, K=8) = 1.837, Lower Critical Value = 1.401.

Table 4.1 also displays several test statistics that indicate the performance of the full model, which can be used for comparison as modifications are made to the original model. For a subsequent model to be deemed superior, the estimation should result in a reasonable R^2, relatively smaller mean absolute percent error (MAPE), an appropriate Durbin-Watson statistic (DW) for the number of observations and parameters, and a relatively smaller Schwarz Information Criterion (SIC), which indicates a more parsimonious model. Although the current model has reasonable test statistics (i.e. R^2 and DW), refining the model will likely provide a lower SIC and MAPE.

Although T^2 and T^3 were hypothesized to capture the trends and movements in the percent of acreage planted, neither of these variables is significant in the estimation and the magnitude of their coefficients is rather small. Thus, T^2 and T^3 are eliminated from the model, leaving T to help control auto-correlation. Table 4.2 indicates the results of the modifications made to the model.

Overall, the lack of additional time variables improves estimation. All of the coefficients have the expected sign, with the exception of *MR*. In addition, the coefficients for *YR* and $\%A_{t-1}$ remain significant. When considering the goodness of fit statistics, the reduced model provides roughly the same R^2. Furthermore, SIC and MAPE are lower, indicating that the new model is more parsimonious and less variable. However, the DW statistic is slightly smaller than the upper critical value, which indicates there may be autocorrelation present.

Table 4.2. Parameter Estimates and Statistics for Reduced Model, Without Prior

Variable/Test Statistic	Estimate
Constant	-47.644
	(30.145)[a]
$\%A_{t-1}$ (Percent Acres in t-1)	0.738*
	(0.063)
YR (Yield Ratio)	48.861*
	(20.711)
MYR (Milling Yield Ratio)	4.023
	(32.179)
MR (Maturity Ratio)	10.772
	(15.009)
T (Time)	-0.722
	(0.440)
R^2	0.800
SIC	4.937
DW	1.722[b]
MAPE	191.49

*Denotes significance at the 0.05 level.
[a] Numbers in parentheses are standard errors.
[b] Upper Critical Value (T=70, K=6) = 1.768, Lower Critical Value = 1.464.

MYR and *MR* remain insignificant, providing some support to the theory mentioned in the previous chapter, which indicates that producers may tend to focus on quantity over quality. Therefore, *MYR* and *MR* are dropped from the model. Once again, *T* remains to help control for autocorrelation. Table 4.3 displays the estimates of the remaining variables, along with the test statistics.

The changes made appear to provide the best performance of any model tested.[2] $\%A_{t-1}$ and *YR* maintain their significance and both have the appropriate sign. The R^2 continues to indicate a good fit, remaining close to that of the full model. In addition,

[2] Several models were tested where *MYR* and *MR* were left in the regression. However, none provided better overall performance, or a lower SIC, than the model containing only $\%A_{t-1}$, *YR*, and *T*.

the DW statistic shows there is no autocorrelation, while the SIC and MAPE are lower than any of the previous models. With this in mind the reduced model indicated in Table 4.3 will be used in the simulations conducted for a variety without prior information.

Table 4.3. Parameter Estimates and Statistics for Final Reduced Model, Without Prior

Variable/Test Statistic	Estimate
Constant	-41.504*
	(17.870)[a]
$\%A_{t-1}$ (Percent Acres in t-1)	0.749*
	(0.060)
YR (Yield Ratio)	57.094*
	(17.501)
T (Time)	-0.545
	(0.345)
R^2	0.798
SIC	4.825
DW	1.715[b]
MAPE	188.14

*Denotes significance at the 0.05 level.
[a] Numbers in parentheses are standard errors.
[b] Upper Critical Value (T=70, K=4) = 1.703, Lower Critical Value = 1.525.

With Prior

Table 4.4 shows the regression results for the full model with prior information, or test plot data, included. The model proves to be a fairly good fit, with an R^2 of 0.798. In addition, each of the variables has the expected sign, except for *MR*. However, similar to the model without prior information in the previous section, the current estimation produces only one significant variable ($\%A_{t-1}$). It is also important to note that the DW statistic is smaller than the upper critical value, which means autocorrelation may be present.

Table 4.4. Parameter Estimates and Statistics for Full Model, With Prior

Variable/Test Statistic	Estimate
Constant	-20.834
	(29.169)[a]
$\%A_{t-1}$ (Percent Acres in t-1)	0.810*
	(0.083)
YR (Yield Ratio)	8.177
	(17.453)
MYR (Milling Yield Ratio)	16.324
	(25.556)
MR (Maturity Ratio)	16.513
	(14.431)
T (Time)	-1.995
	(4.323)
T^2 (Time^2)	-0.045
	(0.462)
T^3 (Time^3)	0.005
	(0.014)
R^2	0.794
SIC	5.087
DW	1.824[b]
MAPE	193.59

*Denotes significance at the 0.05 level.
[a] Numbers in parentheses are standard errors.
[b] Upper Critical Value (T=70, K=8) = 1.837, Lower Critical Value = 1.401.

Therefore, the full model with prior is modified in the same fashion as the aforementioned model (without prior) to find the best model. Table 4.5 shows the estimation results for the reduced model, which has the best overall performance.[3] All of the coefficients have the correct sign, and the $\%A_{t-1}$, *YR*, and *T* are significant. In

[3] Although only one reduced model is displayed, many models were tested to determine which model yielded the best performance.

addition, the resulting SIC and MAPE values are lower than any of the reduced models tested, while maintaining an R^2 close to that in the full model. Despite the fact that this model produced the best overall performance, the DW statistic is, once again, less than the upper critical value. However, it appears that the potential for autocorrelation is inherent in the model with prior, as the DW statistic is marginal in both the full and reduced models. Nonetheless, the DW statistic for the reduced model displayed in Table 4.5 is above the lower critical value, thus the model is carried into simulation.

Table 4.5. Parameter Estimates and Statistics for Final Reduced Model, With Prior

Variable/Test Statistic	Estimate
Constant	-10.59
	(15.394)[a]
$\%A_{t-1}$ (Percent Acres in t-1)	0.794**
	(0.061)
YR (Yield Ratio)	26.084*
	(14.803)
T (Time)	-0.884**
	(0.351)
R^2	0.776
SIC	4.928
DW	1.636[b]
MAPE	151.73

*Denotes significance at the 0.10 level.

**Denotes significance at the 0.05 level.

[a] Numbers in parentheses are standard errors.
[b]Upper Critical Value (T=70, K=8) = 1.837, Lower Critical Value = 1.401.

Model Comparisons

When comparing the two reduced models, the model without prior information appears to provide better results. Despite the fact that the model with test plot data provides a lower MAPE, it is somewhat substandard due to a higher SIC, lower R^2, and the potential for autocorrelation.

On the other hand, it is important to note the significance of the yield ratio in both models. The strong positive relationship between the yield of a variety, with respect to other varieties on the market, and the percent of total acres planted is important to their survival. As the yield ratio of a variety begins to decline, one can notice a decrease in the percent acres planted to that variety. Thus, competition between varieties, based on yields, contributes to explaining the disadoption of older varieties with yields lower than more current varieties on the market.

Ultimately, both models are simulated and the results are discussed in the last section of this chapter. However, it is important to remember that simulation results from the model relying solely on producer data (without prior) should carry more weight, due to its superior regression results.

Out-of-Sample Performance

Out of sample performance is assessed using the variety Kaybonnet, which had a life cycle spanning from 1995-1999. The model used in comparison to the two estimated models is the historical average, which is essentially the only method available within the rice industry to predict the possible performance of a new variety.[4] Thus, an annual average is used, which is calculated from the percent of acres planted to the six varieties utilized in the model in each year of their life cycle. For example, if one wanted to have some indication of how a new variety might perform in the third year of its life cycle, we could look at the average of the old varieties' performance in the third year of their respective life cycles.

With that said, the actual percent of acres planted to Kaybonnet can be used, in conjunction with the predicted percent of acres planted by the historical average model and the two estimated models, to calculate the root mean squared error (RMSE) of each model.

Table 4.6 summarizes the out-of-sample results. Clearly, both of the estimated models have a lower RMSE than the historical average, indicating their superior predictive ability. Furthermore, the model without prior results in the lowest RMSE, lending additional support to the model's strong regression statistics in the previous section. Nonetheless, both models' out-of-sample results are impressive, providing a strong foundation for the simulation of potential varieties.

Table 4.6. Model Comparisons for Out-of-Sample Estimation

Model	RMSE
Historical Average	33.427
Without Prior	6.574
With Prior	8.404

[4]No other predictive life cycle model for rice was discovered when conducting the literature review.

Simulations

The percent of total acres planted to a new rice variety or hybrid is simulated for 100 iterations, using the residuals from the estimated equations. Three scenarios are simulated for both of the estimated models. The first simulation represents a variety that is comparable to the other varieties on the market, indicated by a yield ratio of 1.0. Next, the yield ratio is increased to represent a superior variety with a yield ratio equal to 1.1. Last, a substandard variety is introduced with a yield ratio of 0.9. As mentioned in the methodology, the yield ratio is allowed to remain constant until the variety reaches the third year of its life cycle. After the third year, the yield ratio declines using an inverse beta distribution. Thus, as the yield ratio tapers off, there is an increased level of competition from higher yielding varieties and a higher chance for the disadoption of the current variety.

In addition, due to the lagged variable $\%A_{t-1}$, the prediction for the first year of the life cycle is absent from the regressions and simulations. Thus, the historical average of the percent of acreage planted in the first year for the six varieties included in the model is utilized as a starting point for $\%A_{t-1}$ in the simulations[5]. In other words, the acreage planted in the first year is assumed to be equal to the average performance of past varieties at the onset of their introduction.

In this section, the simulation results for the model without prior are discussed first, followed by the model with prior and a summary of the simulations. The summary

[5] The average percent of total acres planted, across all six varieties, in the first year is equal to 0.4236%.

statistics of the simulated models can be found in Appendix A, along with a tabular representation of the graphs in the following sections.

Without Prior

Figure 4.1 displays a fan graph of the simulation results for a new variety that is introduced with a yield ratio comparable to the other varieties on the market. The fan graph shows the average percent of total acres planted (black line), with the distribution of the data about this average. The bands surrounding the average can be likened to a confidence interval. For example, the outside band, indicated by the brown and red dotted lines, show a 90 percent confidence interval for the simulated data. In addition, the inner band, indicated by the green and blue dotted lines, represents a 50 percent confidence interval. Ultimately, the fan graph provides a visual representation of the probability distribution associated with the simulated data.

As can be seen in Figure 4.1, the average length life cycle of a new variety with a yield ratio of 1.0 is approximately 10 years. However, by the time the variety reaches the eighth and ninth years of its life cycle, there is 5 and 25 percent chance that the variety will no longer be planted, respectively. It is also important to note that the average market share for the variety peaks at 42 percent in year four of the life cycle. Therefore, while seed companies can still generate revenue in the years after the life cycle peaks, a great deal of the marketing and sales efforts may be more beneficial if they are focused on the first four years of the product's existence.

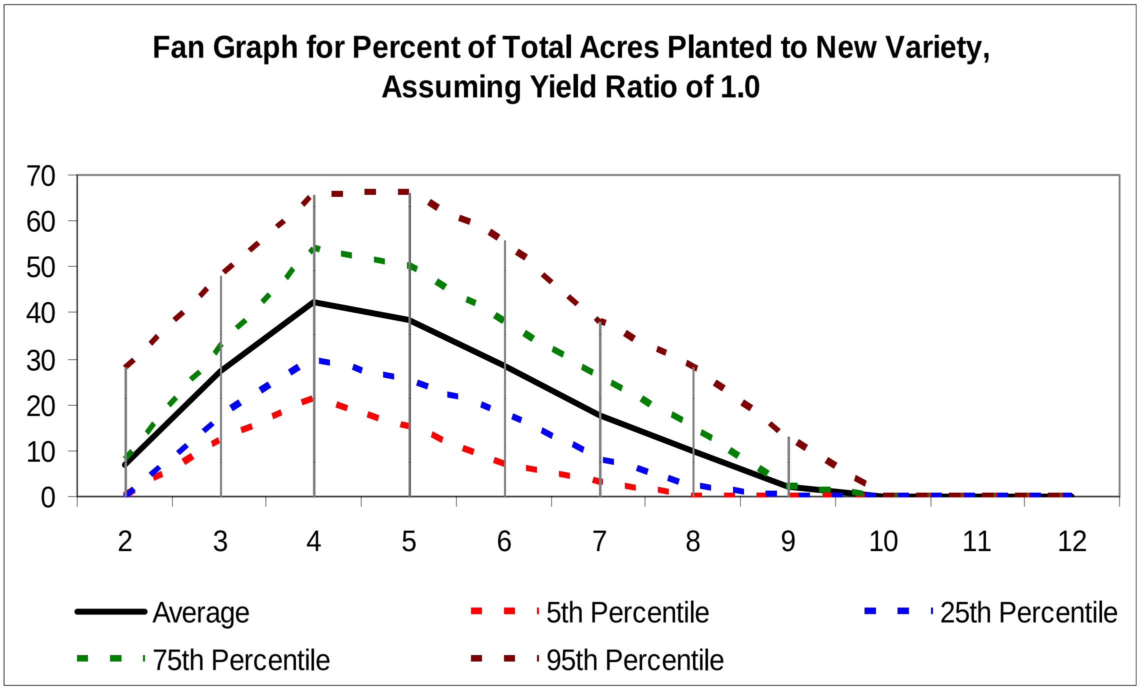

Figure 4.1. Life cycle of a new variety with a yield ratio of 1.0, without prior

Figures 4.2 and 4.3 display the life cycle of a superior and substandard variety, respectively. When considering the opposite ends of the spectrum, one can begin to see the strong influence yield, relative to the industry standard, has on the life cycle. Although both scenarios peak in year four, their average market shares are quite different. A superior variety can expect to see a peak market share of 54 percent on average, while the substandard variety achieves a peak market share of only 31 percent.

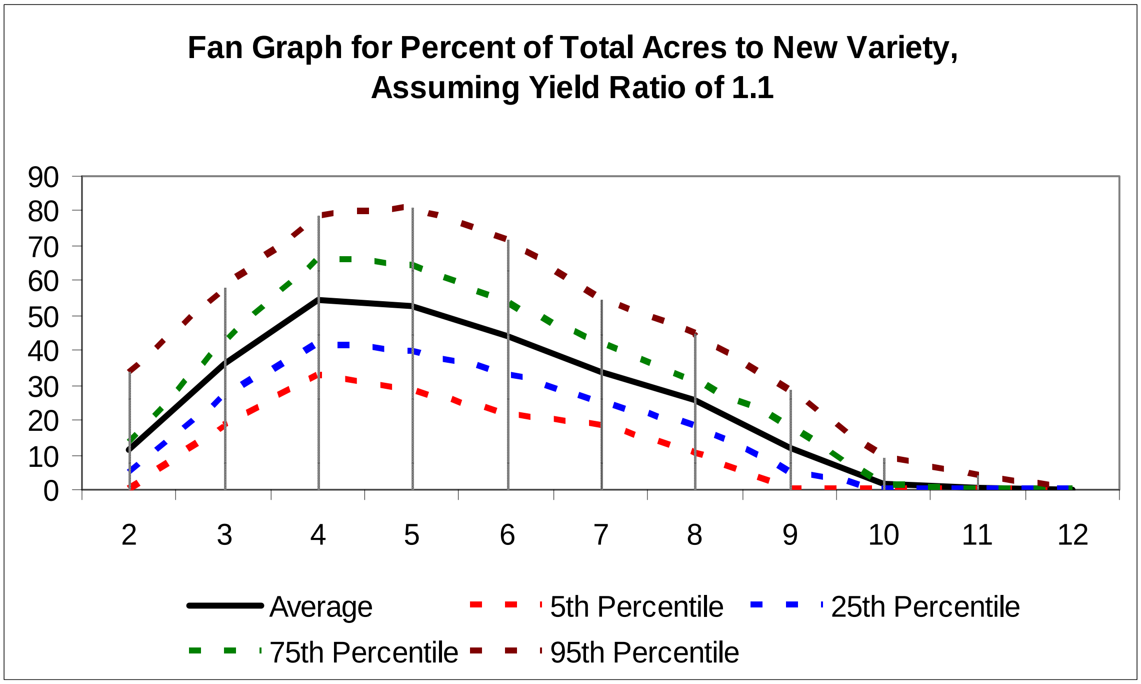

Figure 4.2. Life cycle of a new variety with a yield ratio of 1.1, without prior

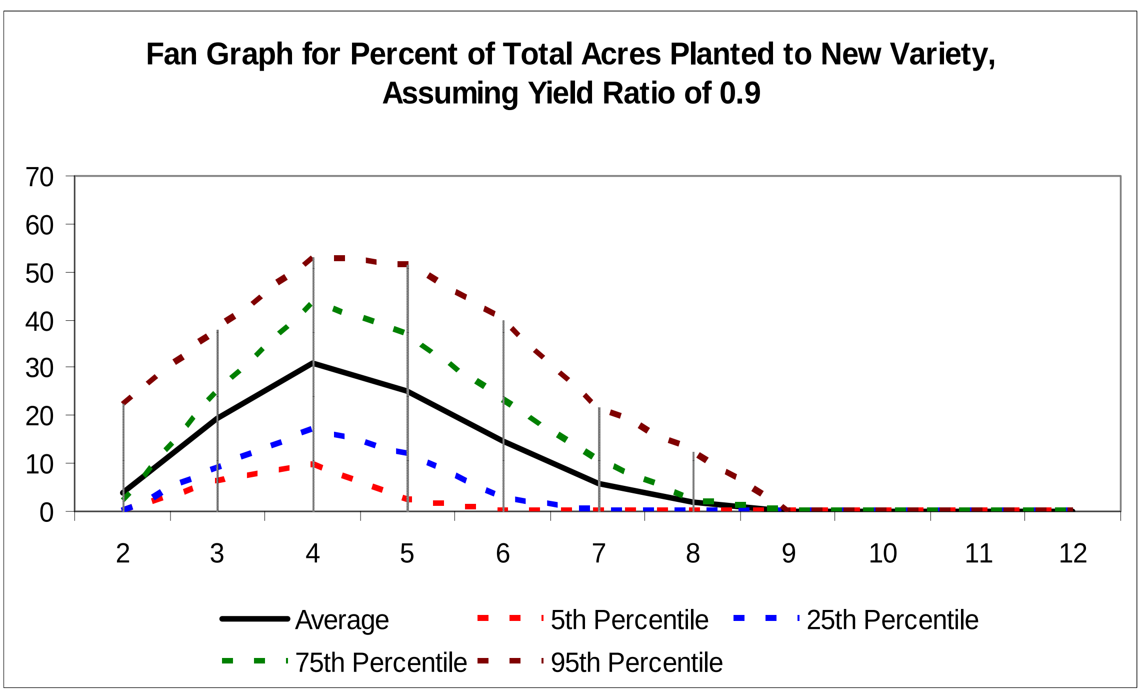

Figure 4.3. Life cycle of a new variety with a yield ratio of 0.9, without prior

Furthermore, there are a couple of large differences between the superior and substandard varieties. The average length of the superior variety's life cycle stretches to approximately 12 years. However, the life cycle of the substandard variety will last only 9 years, on average. If one considers the probability distribution surrounding the average life cycle, it is clear that the substandard variety displays an even less optimistic situation. A variety with a yield ratio of 0.9 will have a 5 percent chance of reaching zero acres planted by year 6 and a 25 percent chance by year 7. On the other hand, a variety with a yield ratio of 1.1 does not realize a 5 percent possibility for zero acres planted until year 9. Thus, the yield ratio proves to be a rather sensitive variable and appears to have a great deal of influence on the percent of acres planted to a new variety.

With Prior

Figure 4.4 shows the fan graph from the simulation of a comparable variety, with prior information. The average life cycle of a variety with a yield ratio of 1.0 is approximately 12 years, coupled with an average peak market share of 39 percent in year 4. Although the longer life cycle seems quite optimistic, the probability distribution about the life cycle indicates that there is a five percent chance that there will be zero percent acres planted to the variety by the eighth year, along with a 25 percent chance in the tenth year.

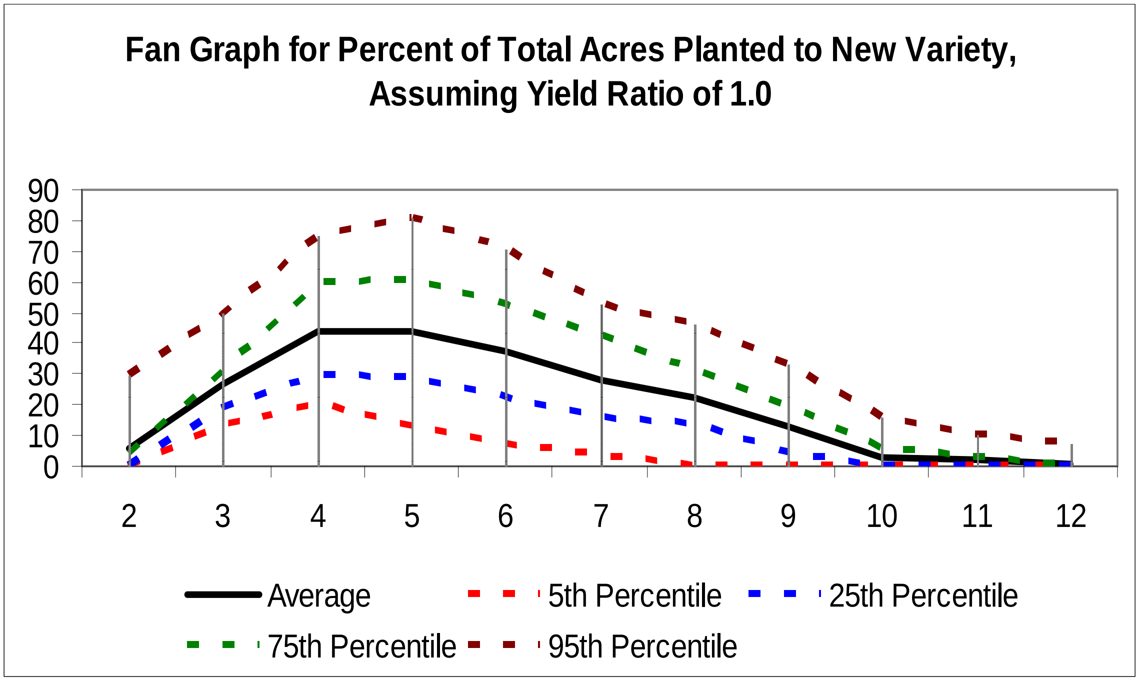

Figure 4.4. Life cycle of a new variety with a yield ratio of 1.0, with prior

Figures 4.5 and 4.6 provide the simulated life cycles for a superior variety and substandard variety, respectively. Once again, comparing the superior and substandard varieties indicates the strong response of percent acres planted to changes in the yield ratio. To begin with, the superior variety obtains an average peak market share of 51 percent in year 5, while the substandard variety reaches a peak market share of 39 percent in year 4. Although, the average market share of the two varieties reaches a peak at similar points in time, the superior variety clearly dominates, holding a higher market share for several years.

Also, there is a stark difference in the length of the life cycle for the two varieties. A variety with a yield ratio of 1.1 displays a life cycle of more than 12 years, on average. Alternatively, a variety with a yield ratio of 0.9 leads to a life cycle that is near its completion in year 10. When considering the probability distribution about the average life cycle, the differences between the two varieties are even more defined. The superior variety's life cycle holds strong and does not show a possibility for zero percent acres planted until year 9. On the other hand, the substandard variety possesses a more variable distribution, with a 5 and 25 percent chance of having zero acres planted in years 6 and 9, respectively. Thus, the fact that the yield ratio has a great deal of influence on the percent of acres planted to a new variety is reinforced with these results.

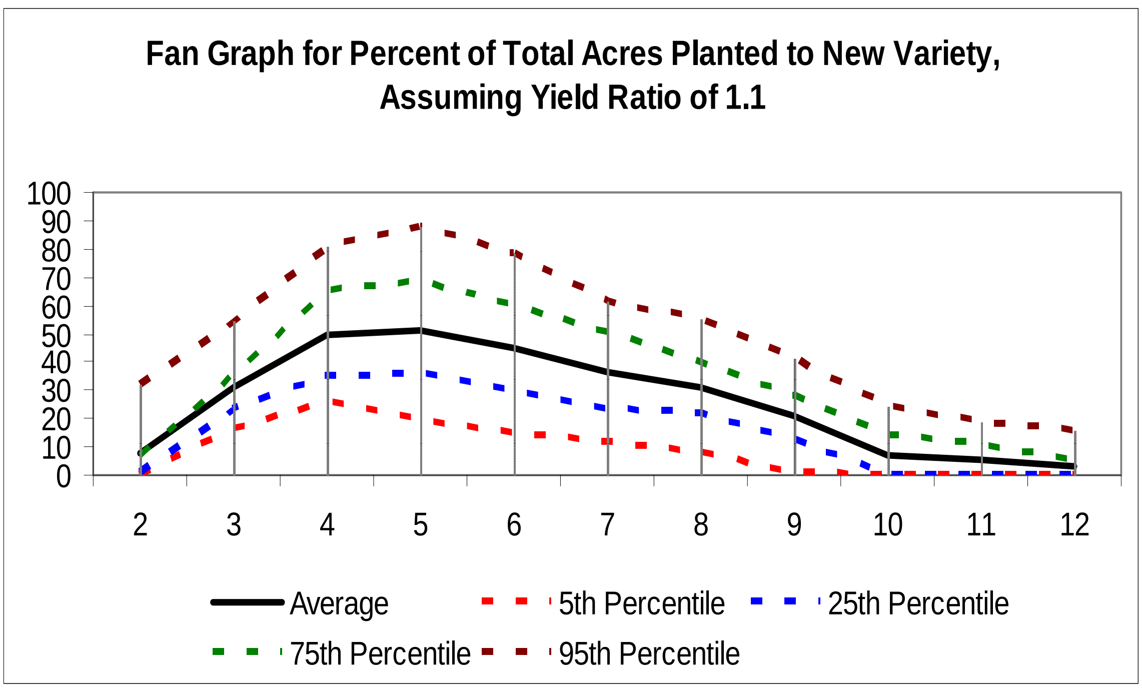

Figure 4.5. Life cycle of a new variety with a yield ratio of 1.1, with prior

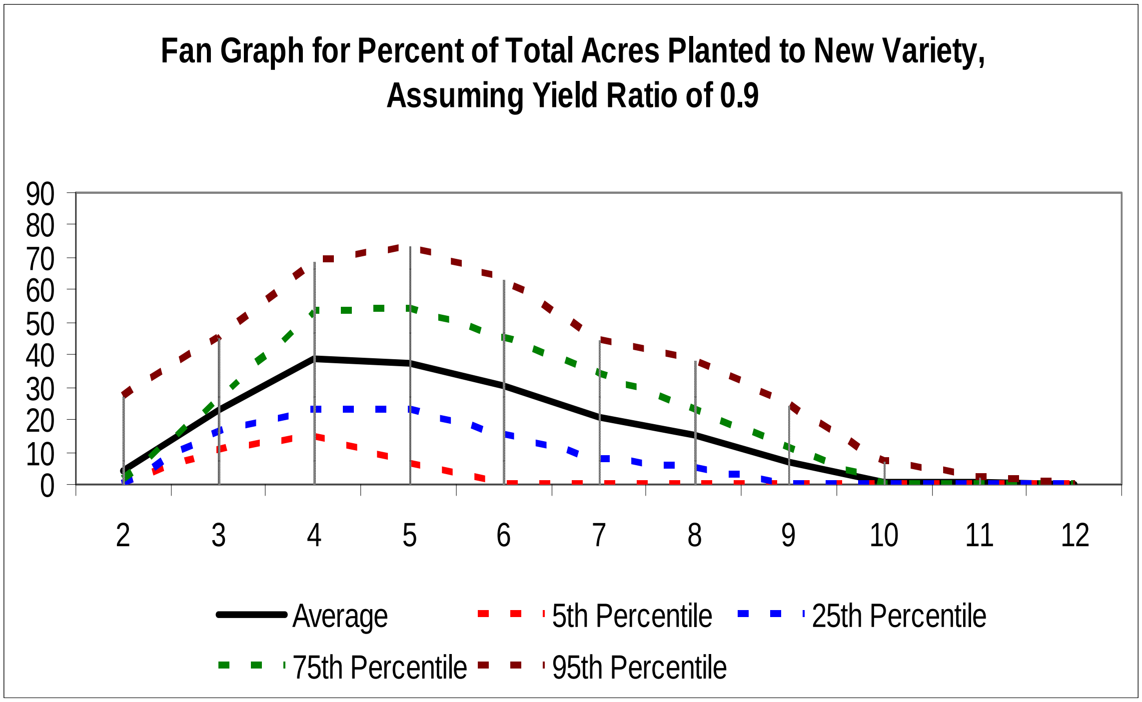

Figure 4.6. Life cycle of a new variety with a yield ratio of 0.9, with prior

Summary

The application of simulation allows decision makers to view the wide range of possibilities for a variety's life cycle and potential return on investment. As was discussed in the previous sections, there are numerous scenarios surrounding the point forecasts and predictions that decision makers typically utilize. Thus, the simulation results provide a more robust prediction of a variety's potential cumulative adoption and disadoption path, by incorporating the uncertainty inherent in each year of the product's life cycle.

Perhaps the most interesting thing to note is that the life cycle peaks in year 4 or 5 for both models. This indicates that firms may want to focus a great deal of attention on the first five years of a variety's life cycle to capitalize on the growing market share. However, there are some interesting differences between the two models. The simulation results indicate that prior knowledge about a variety's potential yield can lead to a longer life cycle, when compared to the model lacking prior information. On the other hand, the model without prior information consistently provides a higher average market share in the peak year.

The longer life cycle generated by the model with prior information seems to indicate that the industry may benefit from some knowledge of the variety's performance before its introduction, provided by the test plot data. Therefore, if performance statistics are widely released and the varieties are marketed appropriately, the length of the life cycle may be increased over time. Although this follows logic, the simulation results of the model with prior should not be blindly accepted over the model without prior, due to its poorer performance in estimation and out-of-sample analysis.

The fact that the model without prior information resulted in a shorter life cycle, overall, agrees with recent life cycle trends. As mentioned in the methodology, the life cycle of new rice varieties appears to be shortening. In addition, varieties that provide superior yields tend to reach a higher peak market share than that predicted by the model with prior information. Thus, while the model without prior may seem less optimistic in terms of life cycle length, it seems to fit the current situation, where varieties achieve a peak market share rather quickly and then taper off.

CHAPTER V

SUMMARY AND CONCLUSIONS

The development of high performance varieties has revolutionized the rice industry in Texas and the United States. After the successful introduction of high yielding semi-dwarf varieties in Texas during the 1980's, the rice industry continued to realize the tremendous potential of research and development. Higher yielding varieties have provided the growers with greater levels of production on fewer acres of land. Thus, there has been a surge in the search for new varieties that can maintain high yields and have higher levels of performance in other areas.

As more varieties have been introduced, the length of time that any one variety remains in the market has continued to decrease due to competition. Therefore, with the large time and capital investments that accompany the development of each new variety, it becomes critically important to be able to preview the length of a new variety's life cycle. This study sought to develop a model to be used in the prediction of a potential variety or hybrid, giving decision makers a tool for use in investment and marketing decisions.

Objective

The objective of this study was to predict the cumulative adoption and disadoption of rice varieties and hybrids, while incorporating the effects of competition among varieties. This study analyzed some of the factors that are commonly viewed as determinants of cumulative adoption and disadoption. In addition, simulation techniques were utilized to provide a more robust prediction of a new variety or hybrid's life cycle.

Procedures

A cross-sectional regression model was formulated to predict the percent of acres planted to a new variety. Annual data on the percent of acres planted to six varieties was utilized as the dependent variable. The independent variables were several ratios, based upon performance characteristics of each variety, such as yield, milling yield, and days to maturity. In addition, three time variables, which were a function of the number of years a variety had been in existence, were also included in the model as independent variables.

Two models were estimated in the study. The first model (without prior) utilized producer survey data to calculate the performance ratios, meaning that the life cycle of a variety was dependent upon collective producer experience. The second model (with prior) used test plot data to calculate the ratios in the first two years of a variety's existence, after which producer survey data was used. Thus the test plot data provided some level of prior experience, which was then updated with industry experience.

The estimated equations were then utilized to simulate the life cycle of new varieties and hybrids. A separate empirical distribution was created for each year of the life cycle using the residuals of the six varieties included in the model estimation. Ultimately, three scenarios were simulated for both models, which predicted the life cycle of a new variety that was comparable, superior, or substandard to the other varieties on the market.

Results

The models were refined to find the model that provided the lowest SIC, which indicates a higher level of parsimony. The most favorable reduced form of both models included $\%A_{t-1}$, *YR*, and *T*. The comparison of the estimation of the two models revealed that the model without prior information performed better, resulting in a higher R^2, lower SIC, and better DW statistic. In addition, the model without prior information performed better in out-of-sample analysis, lending additional support to the superiority of the model.

The significance of the yield ratio proved the importance of including competition in the model. It is clear from the model estimations, that there is a positive relationship between the percent of acres planted and the yield ratio. As the yield ratio continually declines, indicating the presence of higher yielding varieties, the variety experiences disadoption. Thus, direct competition between products, based upon performance characteristics, is important and should be considered as a major factor in explaining the cumulative adoption and disadoption products.

Simulations of the two models provided interesting results. Both models yielded a life cycle that consistently peaked in year 4-5, indicating that decision makers may need to focus a great deal of their attention on the first 5 years of the life cycle to maximize the benefits of a growing market share. On the other hand, the two models provided different results pertaining to the length of the life cycle and the magnitude of the average peak market share. The model with prior information resulted in a longer average life cycle across the three yield ratio scenarios. However, the model without prior information consistently achieved a larger peak market share. Due to superior performance in estimation and the current trend of shortening life cycles of varieties introduced in the rice industry, the model without prior seems to provide more realistic simulation results.

Conclusions

The rice industry contributes a great deal to the economic viability of the Texas Gulf Coast. Rice acreage has decreased significantly over the past thirty years. Thus, the development of performance enhanced rice varieties and hybrids, resulting in higher yields, are important to the survival of the industry.

This study has made significant contributions to the literature through the creation of a model that predicts the entire life cycle of a new variety or hybrid. While most prior studies focused on using a logistic function to estimate the growth rate, or diffusion, of class of products, the research conducted in this study moved in a different direction. To begin with, special attention was paid to incorporating the possibility of disadoption and the effects of competition between specific “brands” of a product, namely types of rice seed. In addition, the use of simulation provided a more robust prediction, allowing one to see the probability distribution associated with the predicted life cycle. Finally, the incorporation of data collected during the development of the rice varieties provided the opportunity to estimate two models: one that focused solely on industry experiences and one that provided prior information that was updated with field level experience.

The better performance of the model without prior in estimation seems to indicate that producers rely a great deal on their own experiences. However, this does not discount the usefulness of test plot data. Obviously, the test plot data is extremely useful to breeders in developing better varieties. Furthermore, test plot data serves as a relative benchmark of how a new variety will perform. Although the test plot data may not be a direct reflection of how the variety will perform in the field, it does provide the industry with some idea of the variety's performance, relative to the test plot data of older varieties.

Additional Research

Due to the fact that only a limited number of observations were available for the producer data, the average of the observations was used to calculate the performance ratios. However, if additional data were available, a time series analysis could be conducted which would provide and different perspective to the study. In addition, the acquisition of survey data pertaining to different locations across Texas would allow for the yield stability ratio to be included in the model.

One the most important relationship excluded from the model is the effect of word-of-mouth communication on the percent of acres planted to a new variety. Farmers are traditionally known as being a communicative group. Thus, the experiences of one farmer could be imposed on another, thereby changing prior perceptions. Although the inclusion of a word-of-mouth variable would likely enhance the model, the effect of communication is hard to quantify. Future research, where primary data is collected to measure the word-of-mouth effects on the life cycle of new rice varieties, would be highly useful to breeders and seed companies.

Another beneficial area of research would be determining other product characteristics that influence the cumulative adoption and disadoption of rice. For example, how do performance characteristics such as cooking quality, disease and insect resistance, fertilizer requirements, and herbicide resistance affect the life cycle. While test data are available for these many of these characteristics, there are no data indicating the varieties' actual performance in the field. Such a data set would be extremely useful in assessing the producer acceptance of varieties and hybrids.

Furthermore, additional research is needed that compares test plot and producer data. If there is a significant difference between research and field data, an analysis could be conducted to determine how producers adjust their expectations based upon the information provided by the test plot data.

Finally, future research is needed to assess the economic implications associated with the life cycle length of a new variety. A model incorporating factors such as research and development costs, seed production and marketing costs, and sales revenue could provide the potential to estimate the economic success of a new variety. In addition, one could determine the level of performance necessary, relative to the competition, to provide substantial return on investment when a new variety is introduced.

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APPENDIX A

SUMMARY STATISTICS FOR SIMULATED MODELS

SUMMARY STATISTICS FOR PROBABILITY DISTRIBUTIONS

Without Prior

Comparable Variety

Table A.1. Summary Statistics for Simulation of New Variety Without Prior, YR of 1.0

	Year										
Variable	2	3	4	5	6	7	8	9	10	11	12
Mean	6.7	27.2	42.2	38.5	28.5	17.8	10.1	2.3	0.0	0.0	0.0
StDev	8.9	10.7	15.3	16.3	14.4	11.2	9.3	4.8	0.0	0.0	0.0
CV	132.1	39.4	36.2	42.4	50.5	63.1	92.1	206.9	0.0	0.0	0.0
Min	0.0	11.8	12.9	7.4	2.2	0.0	0.0	0.0	0.0	0.0	0.0
Max	28.2	51.9	78.2	78.5	63.8	43.8	41.5	25.7	0.0	0.0	0.0

Table A.2. Summary Statistics for Probability Distribution of New Variety Without Prior, YR of 1.0

	Year										
Percentile	2	3	4	5	6	7	8	9	10	11	12
Average	6.7	27.2	42.2	38.5	28.5	17.8	10.1	2.3	0.0	0.0	0.0
5th %	0.0	11.9	21.3	15.3	6.9	3.1	0.0	0.0	0.0	0.0	0.0
25th %	0.0	17.2	30.0	25.2	18.2	8.4	2.2	0.0	0.0	0.0	0.0
75th %	8.0	32.9	54.0	50.0	38.2	25.8	15.2	2.3	0.0	0.0	0.0
95th %	28.2	47.8	65.6	66.3	55.7	38.1	28.1	12.8	0.0	0.0	0.0

Superior Variety

Table A.3. Summary Statistics for Simulation of New Variety Without Prior, YR of 1.1

	Year										
Variable	2	3	4	5	6	7	8	9	10	11	12
Mean	11.3	36.3	54.5	52.7	44.0	33.8	25.7	12.2	1.5	0.5	0.0
StDev	9.9	11.4	15.4	16.5	14.5	11.4	10.2	9.2	3.1	1.7	0.2
CV	87.1	31.4	28.3	31.3	33.0	33.6	39.8	75.8	212.6	309.9	730.3
Min	0.0	17.6	25.5	21.9	17.8	14.0	6.4	0.0	0.0	0.0	0.0
Max	33.9	61.9	91.0	93.2	79.6	60.2	58.0	41.9	14.2	9.5	1.6

Table A.4. Summary Statistics for Probability Distribution of New Variety Without Prior, YR of 1.1

	Year										
Percentile	2	3	4	5	6	7	8	9	10	11	12
Average	11.3	36.3	54.5	52.7	44.0	33.8	25.7	12.2	1.5	0.5	0.0
5th %	0.0	18.5	32.8	28.3	22.1	18.5	10.1	0.0	0.0	0.0	0.0
25th %	5.3	26.9	41.7	39.4	33.2	24.7	18.1	5.3	0.0	0.0	0.0
75th %	13.7	42.9	66.7	64.0	53.5	41.8	31.2	18.6	1.4	0.0	0.0
95th %	33.9	57.8	78.4	81.1	71.5	54.5	44.5	28.7	9.3	4.2	0.0

Substandard Variety

Table A.5. Summary Statistics for Simulation of New Variety Without Prior, YR of 0.9

	Year										
Variable	2	3	4	5	6	7	8	9	10	11	12
Mean	3.7	19.2	30.9	24.9	14.5	5.7	2.0	0.2	0.0	0.0	0.0
StDev	7.1	9.6	15.3	16.0	12.9	7.6	4.5	1.1	0.0	0.0	0.0
CV	190.2	50.0	49.4	64.0	89.0	133.1	226.2	694.7	0.0	0.0	0.0
Min	0.0	6.1	3.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Max	22.5	42.0	65.3	63.8	47.9	27.5	25.1	9.4	0.0	0.0	0.0

Table A.6. Summary Statistics for Probability Distribution of New Variety Without Prior, YR of 0.9

	Year										
Percentile	2	3	4	5	6	7	8	9	10	11	12
Average	3.7	19.2	30.9	24.9	14.5	5.7	2.0	0.2	0.0	0.0	0.0
5th %	0.0	6.1	9.5	2.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0
25th %	0.0	9.0	17.2	12.1	2.8	0.0	0.0	0.0	0.0	0.0	0.0
75th %	2.3	25.2	43.6	36.7	23.1	10.6	2.2	0.0	0.0	0.0	0.0
95th %	22.5	37.8	53.0	51.6	39.9	21.8	12.3	0.0	0.0	0.0	0.0

With Prior

Comparable Variety

Table A.7. Summary Statistics for Simulation of New Variety With Prior, YR of 1.0

	Year										
Variable	2	3	4	5	6	7	8	9	10	11	12
Mean	5.6	26.6	44.2	44.2	37.6	28.1	22.5	13.1	2.9	2.2	0.8
StDev	9.2	10.0	18.8	20.8	19.2	15.7	13.7	10.7	5.2	3.7	2.5
CV	163.4	37.7	42.5	47.1	50.9	56.0	61.0	82.0	176.2	171.1	300.1
Min	0.0	12.8	8.5	3.3	3.0	0.0	0.0	0.0	0.0	0.0	0.0
Max	29.5	52.6	87.8	91.6	80.8	65.4	62.8	47.8	21.7	15.5	12.6

Table A.8. Summary Statistics for Probability Distribution of New Variety With Prior, YR of 1.0

	Year										
Percentile	2	3	4	5	6	7	8	9	10	11	12
Average	5.6	26.6	44.2	44.2	37.6	28.1	22.5	13.1	2.9	2.2	0.8
5th %	0.0	13.0	20.2	12.8	7.0	3.8	0.0	0.0	0.0	0.0	0.0
25th %	0.0	19.0	29.2	29.0	22.0	15.6	13.4	4.1	0.0	0.0	0.0
75th %	4.1	31.0	59.5	60.8	52.5	42.3	31.0	19.5	5.4	2.7	0.1
95th %	29.5	49.9	74.6	80.5	70.6	52.6	46.3	32.8	15.7	10.1	7.5

Superior Variety

Table A.9. Summary Statistics for Simulation of New Variety With Prior, YR of 1.1

	Year										
Variable	2	3	4	5	6	7	8	9	10	11	12
Mean	7.5	30.7	49.9	51.0	45.2	36.1	30.7	20.8	7.3	5.4	3.4
StDev	9.7	10.3	18.9	20.9	19.2	16.0	14.1	11.8	8.1	6.9	4.9
CV	129.8	33.7	37.9	41.0	42.6	44.2	46.0	57.1	111.8	127.0	147.0
Min	0.0	15.4	13.0	9.2	9.9	2.7	2.6	0.0	0.0	0.0	0.0
Max	32.1	57.3	94.0	95.0	88.8	73.8	71.3	56.4	30.3	23.9	20.8

Table A.10. Summary Statistics for Probability Distribution of New Variety With Prior, YR of 1.1

	Year										
Percentile	2	3	4	5	6	7	8	9	10	11	12
Average	7.5	30.7	49.9	51.0	45.2	36.1	30.7	20.8	7.3	5.4	3.4
5th %	0.0	16.2	25.4	19.2	14.9	11.8	7.9	0.9	0.0	0.0	0.0
25th %	0.5	23.0	34.8	35.5	29.5	23.5	21.7	12.5	0.0	0.0	0.0
75th %	6.7	35.7	65.4	67.9	59.9	50.4	39.5	28.1	14.0	10.7	4.7
95th %	32.1	54.6	80.8	87.7	78.5	60.9	54.9	41.4	24.2	18.4	15.5

Substandard Variety

Table A.11. Summary Statistics for Simulation of New Variety With Prior, YR of 0.9

	Year										
Variable	2	3	4	5	6	7	8	9	10	11	12
Mean	4.1	22.8	38.8	37.6	30.2	20.5	15.1	6.7	0.7	0.4	0.1
StDev	8.6	9.6	18.7	20.6	18.9	15.0	12.4	8.7	2.5	1.2	0.6
CV	206.6	42.2	48.2	54.8	62.4	73.0	82.3	129.4	350.0	266.2	586.5
Min	0.0	10.2	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Max	26.8	47.9	81.6	84.3	72.9	57.1	54.2	39.3	13.2	7.3	4.6

Table A.12. Summary Statistics for Probability Distribution of New Variety With Prior, YR of 0.9

	Year										
Percentile	2	3	4	5	6	7	8	9	10	11	12
Average	4.1	22.8	38.8	37.6	30.2	20.5	15.1	6.7	0.7	0.4	0.1
5th %	0.0	10.2	14.3	6.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0
25th %	0.0	15.9	23.1	22.9	14.9	7.7	4.9	0.0	0.0	0.0	0.0
75th %	1.5	26.6	53.6	54.2	45.1	34.2	23.0	10.9	0.0	0.1	0.0
95th %	26.8	45.2	68.4	73.2	62.7	44.4	37.8	24.2	7.2	1.7	0.0

VITA

Stefphanie Michelle Gambrell was born to Gary and Mary Gambrell on November 8, 1979 in Texas City, Texas. Upon graduating from Alvin High School in May 1998, she attended Texas A&M University and received a B.S. degree in agricultural economics in August 2002.

After completing her undergraduate degree, Stefphanie served as an intern at the United States Department of Agriculture and entered the master's program in agricultural economics at Texas A&M University. As a master's student, Stefphanie was employed as a research assistant with the Agricultural and Food Policy Center and served as the recruitment chair with the Graduate Student Association. In addition, she was chosen to present a paper at the American Agricultural Economics Association Annual Meeting in Denver, Colorado in August 2004. Stefphanie completed her master's degree in December 2004.

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